Integrating a participatory approach with simulation modelling to improve smallholder maize systems in the Rift Valley of Ethiopia

by

Tewodros Mesfin Abebe, M.Sc. (Agronomy)

School of Land and Food

Submitted in fulfilment of the requirements for the Doctor of Philosophy (Agriculture)

University of Tasmania October, 2017

Declarations

This is to certify that:
This thesis contains no material which has been accepted for a degree or diploma by the University or any other institution and to the best of my knowledge contains no material previously published or written by any other person, except where duly acknowledged in the thesis.

This thesis may be made available for loan and limited copying and communication in accordance with the Copyright Act 1968.

The research associated with this thesis abides by the international and Australian codes on human and animal experimentation, the guidelines by the Australian Government's Office of the Gene Technology Regulator and the rulings of the Safety, Ethics and Institutional Biosafety Committees of the University.

Tewodros Mesfin Abebe
University of Tasmania
October, 2017

Acknowledgements

It is not possible to complete this dissertation without the genuine support and generous help from a number of people to whom I wish to express my sincere gratitude.

First of all, I would like to thank my major supervisor, Dr Carina Moeller, for giving me the opportunity of doing a PhD with her, and for keeping my focus on the bigger picture. I would like to express my deep and sincere gratitude to all my supervisors, Dr Carina Moeller, Dr David Parsons, and Prof. Holger Meinke for their great dedication, enthusiasm and unrelenting guidance without which this work would have been impossible. You really have been the best supervisors I could have wished for.

I am indebted to the Australian Department of Foreign Affairs and Trade (DFAT) for funding this PhD study through its Australia Awards Program. Many thanks go to all staff members and my fellow office member at the School of Land and Food in UTAS for providing me an adequate working atmosphere and friendly company during my stay in Hobart. Many thanks to Chris Dillon, Sharmila Prajit, and Andrea Riseley, who offered their time and commitment with excellent service and support, as International Scholarship officers in UTAS. I thank the Ethiopian Institute of Agricultural Research, particularly the Melkassa Agricultural Research Centre for facilitating my research.

I express my profound gratitude to farmers of the Bosset and Adamitulu Jido-Kombolcha districts in Ethiopia for their time and willingness to give valuable information during the survey. I wish to thank the agriculture administrators and extension officers in the districts for their help in selecting the study villages and for recruiting participating farmers for the interviews. I wish to acknowledge Mr. Aleligne Assefa for his valuable contribution in helping with the data collection from the field experiment at Melkassa, Ethiopia.

My special thanks go to my wife Etalem and my children Adonias, Danawit, Kidus, and Elsabet for their patience, comprehension and strength during my regular absence; to my mother and my father for inspiring in me confidence to proceed; to my brothers and sisters for their love and support throughout my life; to my friends and other family members in

Ethiopia and Australia for their kindness, encouragement, and continued support and assistance throughout my PhD study.

I also thank all those who supported me in one way or another but are not mentioned here. Above all, I am grateful to the Almighty God, for his protection, strength, courage and wisdom, He has brought me this far!

Abstract

A systems approach in research offers to examine the bio-physical constraints and decision-making of farmers exposed to climate variability. In this project, a systems perspective was achieved by combining computer-based simulation modelling, farmer surveys, and field experimentation to explore current and potential agronomic management practices crucial to smallholder maize (*Zea mays* L.) farmers to manage climate risks in the semi-arid regions of Ethiopia. The study aimed at investigating a suit of management options to identify opportunities that can improve crop productivity while reducing the production risk in smallholder maize-based cropping systems in the Central Rift Valley (CRV) Ethiopia.

To establish better insights into farmers' perceptions of, and management responses to climate variability, farmer surveys or rapid rural appraisal (RRAs) were conducted. The RRAs were conducted in three villages from two districts (Bosset and Adamitulu Jido-Kombolcha (AJK) in the CRV region of Ethiopia. Information collected from the interviews of 60 farmers and two focus group discussions in the study area were used to acquire baseline information of how farmers in the CRV perceive climate variability, particularly rainfall variability, and how their understanding of climate variability translates into farm management decisions and actions. During RRAs, assessments were made regarding farmers' perceptions of the local climate variability, along with how farmers' observation and knowledge of the seasonal climate affect their agronomic decisions. Generally, farmers gave similar criteria to describe seasonal climatic conditions and to distinguish seasons as 'good', 'average' or 'bad' indicating a shared experience. Farmers' perceptions of seasonal climate variability and risk were mainly related to seasonal rainfall parameters in regards to crop growth and yield. Furthermore, in most cases, farmers' ratings of season 'types' were in agreement with the official classification published by the National Meteorological Service of Ethiopia. Of the rainfall characteristics, total amount of seasonal rainfall was rated less critical than variations in the timing of rainfall onset and dry spells during the growing season. The historical pattern, local weather observations, and other indicators allowed farmers to form expectations of what the rainfall conditions are likely to be in the season ahead. Many of the farmers agronomic decisions are based on the actual and expected seasonal rainfall, however, not all farmers respond in the same way. Farmers indicated that rainfall indicators are particularly important as many of the key management decisions (i.e.,

sowing date, cultivar choice, the portion of land allocated to maize and other crop species) are flexible according to the timing of the onset of the seasonal rains. Historically, farmers used to sow their late maturing maize if rain started early in the *Belg* season (March/April–May), however, many farmers stated that they had noticed that the onset and distribution of early seasonal rainfall had become less reliable and more variable from the 1990s onwards. Farmers explained *Belg* season as unreliable due to post-sowing dry spells of varying length that can risk their crop to fail and they often need to re-sow. Still, around 30% of the respondents at Bosset and 60% at AJK opted to sow a late-maturing cultivar if *Belg* rain did occur, while the remaining 60% of farmers would wait until June if rain established well in the *Kiremt* season (June–September). In this study, less than 30% of the respondents applied mineral nitrogen (N) fertiliser, at sub-optimal rates, while 70% did not apply N fertiliser at all. Of the 70% of respondents who did not apply N fertiliser, nearly 40% of the respondents assumed that their fields were sufficiently fertile or non-responsive at all and there would be no yield advantage from applications of commercial N fertiliser.

In 2012, a maize field experiment was conducted season at Melkassa, in the CRV, to obtain a comprehensive quality data set suitable for modelling purposes and to evaluate the responses of two locally adapted maize cultivars to contrasting sowing dates and N fertiliser application rates. Data included daily weather, crop properties (phenology, growth pattern, plant N concentration, grain and biomass yield of the locally adapted and medium-maturing maize cultivar, *Melkassa-2*), soil water and N characteristics and crop management details, along with the initial conditions of the soil profile (soil water and mineral N content and surface residue). These data were used to parameterise the Agricultural Production Systems sIMulator (APSIM) for one of dominant soil type representative of ‘good cropping conditions’ in the region. The parameterised model was evaluated against independent data from six maize experiments conducted between 2006 and 2012 at Melkassa. The model was evaluated by comparing the simulated and observed phenology, grain and biomass yields of maize cv. *Melkassa-2* across a range of production situations at Melkassa. Generally, evaluation of the parameterised model against independent data showed that it was able to predict key crop responses including crop phenology, grain yield and biomass production as evidenced by different statistical indices for the goodness of fit between the simulated and observed values. The results demonstrated that APSIM-Maize is reliable and suitable for scenario analyses of maize production systems in semi-arid environments of Ethiopia.

Subsequently, the APSIM-Maize model was configured to run long-term simulation experiments to explore the maize yield response to agronomic factors, which farmers who participated in the RRAs had identified as being important in managing climate risks. In the long-term simulations, a combination of varying sowing window, cultivar type and N fertiliser rates were considered to represent local management practices of typical farmers. In addition, agronomic recommendations of research and extension services were simulated along with other agronomic management measures. Simulations of maize yield were run for each year of the available historical weather records from weather stations nearby to the study villages (i.e., 34 years ranging from 1982 to 2015 at Adamitulu and 39 years ranging from 1977 to 2015 at Melkassa). For the sowing windows, early, normal and late sowing dates were considered. Cultivar choices included early-, medium- and late-maturing maize cultivars and three rates of N fertiliser were applied: 0 kg N ha^{-1} (N0), 25 kg N ha^{-1} (N25), and 50 kg N ha^{-1} (N50). Altogether, there were 54 simulation scenarios to analyse for both Adamitulu and Melkassa. The production risk associated with each combination of agronomic factors were estimated thereby creating best management options that farmers may possibly consider in the future when making decisions related to maize production under their local environment, which is characterised by highly variable and uncertain climate. Early sowing (March/April–May) ensured a sowing opportunity in more years compared to normal or late sowing, however, the likelihood of complete crop failure was greatest for early sowing (10%), due to a false start of rain or a risk of post-sowing dry spells, with risk decreasing as sowing was delayed from a normal (5%) to late window (<5%) during the *Kiremt* season. For late sowing, crop failure was unlikely, except for the late-maturing cultivar at Adamitulu where crop failure was ~15% more likely. For the early sowing, the late-maturing cultivar out-yielded the earlier cultivars at all levels of cumulative probability in 90% of the years. For the normal sowing, there was at least 88% likelihood of yield gain from selecting late-maturing cultivars compared to earlier cultivars irrespective of the N rate applied. At Adamitulu, the yield advantage of the late-maturing cultivar was greater if sown early (1 March–30 May) instead of later (early- to mid-June or mid- to end-June). At Melkassa, the yield gain was greater if the late-maturing cultivar was sown during the normal (1–15 June) and late (16–30 June) sowing window rather than early (1 April–30 May). For both locations, the long-term median yield of the late cultivar was greater than the early or normal cultivar, especially in high to average yielding years. In contrast, selecting an early cultivar reduced median yield. Irrespective of sowing time, there was at least an 85% likelihood of a yield loss from using an early cultivar than the medium and the late cultivars. However, for the late sowing at

Adamitulu, the likelihood of yield penalties was only 65% when using an early or medium cultivar instead of the late one. Application of N fertiliser produced greater yields compared to unfertilised maize in at least 85% of the years regardless of the sowing window and cultivar type. With application of N50, there was a 65% likelihood that the yield gain would be more than the maximum yield that could ever be achieved with the application of N25. Averaged across locations, application of fertiliser could result in increases in the long-term median yields of 77% at N25 and 133% at N50 (2.7 and 3.5 t ha^{-1} vs. 1.7 t ha^{-1}) compared to the baseline N0. There were large shifts in cumulative distribution functions towards greater yields with application of either N25 or N50 compared to N0, although to varying degrees depending on the sowing time and the cultivar type. For a late cultivar sown at early and normal sowing windows, and for a medium cultivar sown late, the long-term simulations showed that application N25 could increase yield in more than 95% of the seasons without affecting the inter-seasonal variations in yield (as indicated by CV%) compared to N0. On the other hand, the locally recommended rate of N50 reduced maize yields in as much as 20% of the seasons compared to the farmer baseline N application strategy. Farmers are guaranteed a minimum yield of 2.5 t ha^{-1} in 75–90% of the simulated seasons when they applied at least N25, whereas this was only possible in 17–35% of the simulated seasons when no N was applied. Although the application of N fertiliser is not a standard practice in the region, the scenario analyses highlighted the importance of N fertiliser to boost crop productivity without inducing additional inter-seasonal variations. In conclusion, financially constrained and risk-averse farmers in the study areas, who traditionally grow maize without application of commercial N fertiliser, need to be educated about the benefits of using N fertiliser at a modest rate of application (i.e., 25 kg N ha^{-1}). This low risk strategy could be a stepping-stone to feasible intensification of the smallholder maize system in the CRV region.

This thesis demonstrated that understanding the various aspects of the smallholder farmers including their local management situation, aspirations and risk preference and production objectives can be achieved using a participatory research approach. By engaging farmers in focus group discussions and individual interviews, along with crop simulation modelling using APSIM, climatic risks and their interaction with changes in agronomic management decisions and technological strategies for improving the performance of the farm system that suit the biophysical environment and socioeconomic conditions of the farming community can be explored. As a result, relevant and targeted *ex-ante* information can be generated about crop yield responses to various combinations of climate, soil and management factors. This enables researchers to provide farmers and their extension advisors with quantifiable information about production levels and risks as a consequence of the various agronomic management options. Ultimately, this will help support farmers shape their local practices and guide their strategic decisions in the face of climate variability and uncertainty.

Conference publication arising from this research

Tewodros Mesfin, Carina Moeller, David Parsons, and Holger Meinke. 2015. Maize (*Zea mays* L.) productivity as influenced by sowing date and nitrogen fertiliser rate at Melkassa, Ethiopia: parameterisation and evaluation of APSIM-Maize. In Proceedings of the 17th Australian Society of Agronomy (ASA) Conference, 20–24 September 2015, Hobart, Australia. http://www.agronomy2015.com.au/papers/agronomy2015final00437.pdf. (Chapter 5).

Table of Contents

DECLARATIONS .... **I**

ACKNOWLEDGEMENTS .... **II**

ABSTRACT .... **IV**

TABLE OF CONTENTS .... **X**

LIST OF FIGURES .... **XIV**

LIST OF TABLES .... **XVII**

CHAPTER 1 GENERAL INTRODUCTION **1**

1.1. Background **1**

1.2. Problem statement of the study **2**

1.3. Purpose of the study **3**

1.4. Significance and methodological overview of the study **5**

1.5. Main aim and objectives of the study **11**

1.6. Research hypotheses **12**

1.7. Outcomes of the study **13**

1.8. Outline of the thesis **13**

CHAPTER 2 LITERATURE REVIEW **16**

Abstract **16**

2.1. Introduction **17**

2.2. Systems Approaches in Farming System Research **20**

2.2.1. What is a Farming System? 20

2.2.2. Farming Systems Research in Developing Countries 21

2.2.3. Participatory Research 22

2.2.4. Why Use Systems Approaches? 24

2.3. Models and Simulation **27**

2.4. Advancements in Crop Models **29**

2.5. Crop modelling as Part of Participatory Research: Case Studies **31**

2.6. Participatory Modelling for minimising Climate Risk **36**

2.7. Conclusion **38**

CHAPTER 3 FARMERS' PERCEPTIONS, KNOWLEDGE OF, AND RESPONSES TO CLIMATE VARIABILITY IN THE CENTRAL RIFT VALLEY OF ETHIOPIA **42**

Abstract **42**

3.1. Introduction **44**
3.2. Methods **45**
3.2.1. Description of the study area 45
3.2.2. Situation analysis 46
3.2.3. Farming systems 47
3.2.4. Rapid rural appraisals 48
3.2.5. Statistical analysis of survey data 52
3.3. Results **53**
3.3.1. Characteristics of the participants 53
3.3.2. Farmer criteria used to describe past maize growing seasons 54
3.3.3. Perceptions of climate variability and associated risk 57
3.3.4. Management strategies used by farmers in response to varying seasons 64
3.3.5. Awareness and use of seasonal climate forecast information 68
3.4. Discussion **70**
3.4.1. Perception of climate variability and risk 70
3.4.2. Farmers' management strategies 73
3.5. Conclusion **76**
CHAPTER 4 MAIZE (*ZEA MAYS* L.) PRODUCTIVITY AS INFLUENCED BY SOWING DATE AND NITROGEN FERTILISER RATE IN THE CENTRAL RIFT VALLEY OF ETHIOPIA: A DATASET FOR APPLYING A CROP MODEL OF MAIZE GROWTH AND DEVELOPMENT **77**
Abstract **77**
4.1. Introduction **78**
4.2. Materials and Methods **80**
4.2.1. Site Description 80
4.2.2. Experimental Design 81
4.2.3. Crop agronomy 82
4.2.4. Crop data 83
4.2.5. Soil moisture measurements 84
4.2.6. Statistical analysis 85
4.3. Results **86**
4.3.1. Seasonal conditions and crop phenology 86
4.3.2. Grain yield 89

4.3.3. Total biomass and leaf area index....89
4.3.4. Yield components and harvest index....90
4.3.5. Soil water....90
4.4. Discussion....91
4.5. Conclusion....95
CHAPTER 5 MAIZE (*ZEA MAYS* L.) PRODUCTIVITY AS INFLUENCED BY SOWING DATE AND NITROGEN FERTILISER RATE IN THE CENTRAL RIFT VALLEY OF ETHIOPIA: PARAMETERISATION, EVALUATION AND APPLICATION OF APSIM-MAIZE....97
Abstract....97
5.1. Introduction....98
5.2. Materials and Methods....101
5.2.1. Model description....101
5.2.2. Field experiments for model parameterisation and testing....104
5.2.3. Model parameterisation....104
5.2.4. Independent data sets for model evaluation....107
5.2.5. Measures of model performance....108
5.2.6. Simulation scenarios....109
5.3. Results....110
5.3.1. Model evaluation....110
5.3.2. Model application....116
5.4. Discussion....117
5.4.1. Model performance....117
5.4.2. Scenario analyses....120
5.5. Conclusion....123
CHAPTER 6 RISKS AND BENEFITS ASSOCIATED WITH ALTERNATIVE MANAGEMENT PRACTICES IN MAIZE SYSTEMS OF SMALLHOLDER FARMERS IN SEMI-ARID ENVIRONMENTS OF ETHIOPIA....124
Abstract....124
6.1. Introduction....126
6.2. Materials and methods....128
6.3. Results....135
6.3.1. Interactions between management strategies....136

6.3.2. Farmers' management....140
6.3.3. Management recommended by extension services....141
6.3.4. Comparison of farmers' strategies and extension services recommendations....141
6.3.5. Simulated best management practices....142
6.4. Discussion....144
6.5. Conclusion....151
CHAPTER 7 GENERAL DISCUSSION....152
7.1. Summary of the thesis....152
7.2. Methodological limitations of the study, conclusion and the way forward....162
REFERENCE....167
APPENDIX....204
Focus Group Discussion Questions....204
Key-informants Questionnaire....207

List of figures

Figure 3.1: Study districts in the Oromia region of the Central Rift Valley, Ethiopia. 45
Figure 3.2: Number of good, average and bad seasons out of ten seasons as perceived by farmers. Results are grouped by gender, age, education, farm experience and land holding. . 58
Figure 3.3: Farmers' ratings of seasonal rainfall conditions at Bosset (a) and Adamitulu Jido-Kombolcha (b). The ratings in parentheses are based on the classification of the Ethiopian National Meteorology Agency (Korecha and Sorteberg, 2013). 60
Figure 3.4: Farmer estimates of maize grain yield in bad, average, and good seasons (N=60). The boxes show the 25th, 50th (median), and 75th percentile. The whiskers show the 10th and 90th percentile, and yields greater or less than the 10th and 90th percentile are indicated by circles. 61
Figure 3.5: Key management strategies applied by the farmers in response to climate variability in the Bosset and Adamitulu Jido-Kombolcha districts of Ethiopia (see text for details of the various management strategies; (N=60)). 65
Figure 3.6: Type of climate forecasts used in making farming decisions (N=60).................70
Figure 4.1: Climate at Melkassa, Ethiopia (1977–2012): mean monthly rainfall (bars) and mean monthly maximum and minimum temperatures (–). Maize is grown from March until September. 80
Figure 4.2: Seasonal growth conditions for maize sown at two dates (SD1: 6 July; SD2: 20 July) at Melkassa, 2012: cumulative in-crop rainfall (–), cumulative in-crop rainfall plus irrigation (•••), and cumulative thermal time (---) from emergence to silking (S), and physiological maturity (M). 87
Figure 4.3: Total above-ground biomass until harvest under (a) two sowing dates (SD1: 6 July; SD2: 20 July), (b) two nitrogen fertiliser rates (N0: 0 kg N ha^{-1}; N100: 100 kg N ha^{-1}), and (c) changes in green leaf area index (LAI) with N0 and N100 for maize grown at Melkassa in 2012. 89
Figure 4.4: Soil water profiles at different days after sowing (DAS) in maize (cv. *Melkassa-2*) grown at Melkassa in 2012: the sowing dates were 6 July (SD1) and 20 July (SD2), and the nitrogen fertiliser rates were 0 kg N ha^{-1} (N0) and 100 kg N ha^{-1} (N100). 91
Figure 5.1: Soil characteristics at Melkassa: (a) lower (CLL) and upper limit (DUL) of plant extractable soil water, saturated (SAT) and air-dry (AD) soil water content; (b) percentage

organic carbon (OC%) and bulk density (BD), fractions of inert (*finert*), and microbial (*fbiom*) carbon. 106

Figure 5.2: Initial soil conditions: (a) volumetric soil water and (b) NO_3-N for the maize sown on 6 July (SD1) and 20 July (SD2) 2012. 107

Figure 5.3: Rainfall (black bars) and irrigation (grey bars) for maize sown on 6 July 2012 (SD1) and grown at nitrogen fertiliser rates of 0 kg N ha^{-1} (N0) and 100 kg N ha^{-1} (N100), and simulated (lines) and observed (symbols) soil water contents in five soil layers (0–1.20 m depths), Melkassa, Ethiopia. The upper and lower limits of plant available soil water are indicated by the horizontal dotted lines. 111

Figure 5.4: Rainfall (black bars) and irrigation (grey bars) for maize sown on 20 July 2012 (SD2) and grown at nitrogen fertiliser rates of 0 kg N ha^{-1} (N0) and 100 kg N ha^{-1} (N100), and simulated (lines) and observed (symbols) soil water contents in five soil layers (0–1.20 m depths), Melkassa, Ethiopia. The upper and lower limits of plant available soil water are indicated by the horizontal dotted lines. 112

Figure 5.5: Comparison of simulated (lines) and observed (symbols) total above-ground biomass, grain yield, and LAI of maize sown on 6 July 2012 (SD1) and 20 July 2012 (SD2) and grown at two rates of fertiliser nitrogen (N0: kg N ha^{-1}; N100: 100 kg N ha^{-1}) at Melkassa, Ethiopia. Vertical bars represent the standard error of means. 114

Figure 5.6: Observed and simulated(a) days to silking and physiological maturity; (b) grain yield; and above-ground biomass of cv. *Melkassa-2* from six experiments conducted at Melkassa, Ethiopia (2006–2012). Diagonal lines represent the 1:1 fit where y=x. 116

Figure 5.7: Cumulative probability distributions of maize yield (1990–2014) simulated for three sowing windows (May, June, and July) and three nitrogen fertiliser rates (0, 50, and 100 kg N ha^{-1}) at Melkassa, Ethiopia. Horizontal dashed lines represent 25th, 50th, and 75th percentiles and the vertical dashed lines show the median yield for each treatment. 117

Figure 6.1: In-crop rainfall amounts over the simulation period for early sowing (1 March–30 May) at Adamitulu and (1 April–30 May) at Melkassa (a) and for normal and late sowings (1–30 June) at both locations (b). The horizontal lines inside the figures are the long-term average in-crop rainfall amounts for the simulated seasons. 136

Figure 6.2: Cumulative probability distribution for grain yield based on simulation analysis for early sowing of a late-maturing cultivar at 0 kg N ha-1 (ES-LM-N0) and at 50 kg N ha^{-1} (ES-LM-N50), for the normal sowing of a medium-maturing cultivar at 0 N ha^{-1} (NS-MM-N0) and at 50 kg N ha^{-1} (NS-MM-N50), and for the late sowing of an early-maturing cultivar

at 0 kg N ha^{-1} (LS-EM-N0) and 50 kg N ha^{-1} (LS-EM-N50). The intersections between horizontal and vertical lines are for comparing the simulated median yields........................142

Figure 6.3: Probability of a yield gain or loss for an early- and medium-maturing cultivar relative to a late-maturing cultivar (vertical line) when sown at a normal sowing window (1–15 June) with application of N fertiliser at 0 kg N ha^{-1} (a), at 25 kg N ha^{-1} (b), and at 50 kg N ha^{-1} (c). 143

Figure 6.4: Probability of a yield gain or loss for an early- and medium-maturing cultivar relative to a late-maturing cultivar (vertical line) when sown at a late sowing window (16–30 June) with application of N fertiliser at 0 kg N ha^{-1} (a), at 25 kg N ha^{-1} (b), and at 50 kg N ha^{-1} (c)...144

List of tables

Table 3.1: Rainfall statistics from two meteorological stations in the study region. 46
Table 3.2: Summary of information gathered in the focus groups discussions and the interview questionnaire. 50
Table 3.3: Characteristics of households surveyed in the Bosset and Adamitulu-Jido Kombolcha (AJK) districts, Ethiopia. 54
Table 3.4: Different criteria of farmers used to classify different seasonal climatic conditions. 56
Table 3.5: Rating of seasons (1992–2011) for two districts in the Central Rift Valley of Ethiopia. 57
Table 3.6: The importance attributed to various climatic risks that farmers identified in affecting their maize production at Bosset and Adamitulu Jido-Kombolcha (AJK). 64
Table 4.1: Physical and chemical properties of the experimental soil measured prior to the commencement of the maize experiment. One standard error of mean (+/-) is given in parentheses. 81
Table 4.2: Crop phenology, yield components, grain yield, biomass, and harvest index of maize (M-2: cv. *Melkassa-2*; M-3: cv. *Melkassa-3*) sown on two dates (SD1: 6 July 2012; SD2: 20 July 2012), and grown using two nitrogen fertiliser rates (N0: 0 kg N ha^{-1}; N100: 100 kg N ha^{-1}) at Melkassa, Ethiopia. One standard error of mean (+/-) is given in parentheses. The probability of F values for interactions and main effects are provided in the text...88
Table 5.1: Experimental conditions for maize sown at two dates (SD1, SD2), and grown at two rates of fertiliser nitrogen (N0, N100), at Melkassa in 2012: N fertiliser rate, in-crop rainfall, amounts of supplemental irrigation, and dates of application. 104
Table 5.2: Cultivar parameters fitted for APSIM-Maize to simulate the phenological development and kernel growth of cv. *Melkassa-2*. 105
Table 5.3: Experiments and the respective management used for evaluating the performance of APSIM-Maize..108
Table 5.4: Statistical criteria for the goodness of fit between measured and simulated soil water contents in 0–1.2 m soil depth at Melkassa, 2012. 113
Table 5.5: Measured and simulated stover and grain N concentrations of maize sown on 6 July (SD1) and 20 July (SD2), and grown at fertiliser rates of 0 kg N ha^{-1}(N0) and 100 kg N

ha^{-1} (N100) at Melkassa, 2012. Values in parentheses represent the standard error of mean. 115
Table 6.1: APSIM-Maize parameters to simulate cultivars differing in phenology at Adamitulu and Melkassa..130
Table 6.2: Description of simulation scenarios (combinations of sowing window, cultivar type, and N fertiliser rate) for Melkassa and Adamitulu: typical agronomic practices employed by smallholder farmers (1), agronomic recommendations of extension services (2) and alternative management measures (3). 133
Table 6.3: Minimum, average, median, maximum, and coefficient of variation (CV %) of simulated maize grain yields for different sowing windows (early: 1 March–30 May; normal: 1–15 Jun; late: 16–30 Jun), cultivar types (early, medium and late maturing), nitrogen (N) fertiliser rates (0, 25, and 50 kg N ha^{-1}) at Adamitulu. 138
Table 6.4: Minimum, average, median, maximum, and coefficient of variation (CV %) of simulated maize grain yields for different sowing windows (early: 1 April–30 May; normal: 1–15 Jun; late: 16–30 Jun), cultivar types (early, medium and late maturing), nitrogen (N) fertiliser rates (0, 25, and 50 kg N ha^{-1}) at Melkassa. 139

Chapter 1 General Introduction

1.1. Background

Ethiopia's economy depends to a large extent on rain-fed (non-irrigated) agriculture (Thornton et al., 2006; World Bank, 2006; Bryan et al., 2009; Conway and Schipper, 2011; Rosell, 2011). The agricultural sector contributes about 40% of the total GDP (MoFED, 2007), and fluctuations in the performance of the agricultural sector impacts the economy as a whole (World Bank, 2006; MoFED, 2007). Climate variability, particularly seasonal rainfall variability, is a principal source of risk for the economies of many developing countries, including Ethiopia (Thornton et al., 2006; Magombeyi and Taigbenu, 2008). In particular, unreliable rainfall pattern and associated droughts have been reported as a major trigger for food insecurity and poverty in Ethiopia, which is often escalated by complex socio-economic and political factors (Adenew, 2004; von Braun and Olofinbiyi, 2007; Devereux, 2009; Stringer, 2009; Demeke et al., 2011; Rosell, 2011; Shiferaw et al., 2014).

In Ethiopia, crop production contributes more than 60% to agricultural GDP (Mulat et al., 2006). Approximately eight million smallholder farmers grow maize (Zea *mays* L.), followed by about six million tef (*Eragrostis tef* [Zucc.] Trotter) growers and four million wheat (*Triticum aestivum* L.) growers (CSA, 2010; Rashid et al., 2010). Maize is arguably the most important crop in smallholder farming systems of Ethiopia, and the popularity of maize in Ethiopia is partly because of its high value as a food crop as well as the growing demand for the stover as animal fodder and as a source of fuel for rural families. The rapid growth in population will demand more food, and consequently, maize will remain a strategic crop for achieving national food security (Abate et al., 2015).

In Ethiopia, 65% of the total land mass (EPA, 1998) and 46% of the total arable land (Yonas, 2001) are classified as drylands where rainfall variability is inherently high (Bot et al., 2000; Stewart et al., 2006). Of the drylands, semi-arid and dry subhumid areas account for 27% of the total rain-fed crop production in Ethiopia (Temesgen et al., 2009). About 40% of the national maize growing areas fall within the semi-arid and dry-subhumid areas, where fluctuations in annual production are high due to large inter- and intra-seasonal rainfall variability (Biazin and Stroosnijder, 2012; Kassie et al., 2013a). Although large in area, these environments contribute less than 20% to the national maize production (Nigussie et al., 2001). On average, maize yields range from 0.6 to 1.5 t ha^{-1} in dryland areas of Ethiopia compared to the national average maize yield of around 2.2 t ha^{-1} (Nigussie et al., 2001; Tesfaye and Walker, 2004; Araya and Stroosnijder, 2011; Kassie et al., 2013a). Inevitably, tenable agronomic and technological interventions are crucial for effectively managing the impact of climate risk, efficiently utilising the limiting resources (e.g., nitrogen (N) and water), and ultimately closing the yield gap in the dryland region (Muchow et al., 1991; Shamudzarira and Robertson, 2002; Kassie et al., 2014). Moreover, it has been shown that there is a valid argument in encouraging research to focus on technologies that take into account different aspects of the smallholder farmers conditions (i.e., their farming objective, technical skill, resource status, or risk preference) that are adaptable to the specific context of the cultural-behavioural aspects as well as the socio-economic status of the local farmers (Colin and Crawford, 2000; Giller et al., 2009; Darnhofer et al., 2010).

1.2. Problem statement of the study

The Central Rift Valley (CRV) region of Ethiopia is an important agricultural area in the Ethiopian drylands (Biazin and Stroosnijder, 2012; Getnet et al., 2014, 2016). In the past four decades, the Acacia-wooded grasslands of the region have been rapidly converted into cultivated land to meet the demands of a growing population (Rembold et al., 2000; Dessie and Kleman, 2007). Agriculture in the CRV region is dominated by mixed crops and modest livestock production systems, which are the mainstays of livelihoods for households in the region (Biazin and Stroosnijder, 2012). Between 1973 and 2006, the area under arable cropping has more than doubled (Garedew et al., 2009), however, the productivity and profitability of farms are particularly affected by uncertainty in production due to the highly variable seasonal rainfall pattern (Fujisaka et al., 1996a; Biazin and Stroosnijder, 2012; Kassie et al., 2013a and b). In the region, maize is the principal crop and yield reductions of up to 40% can occur due to soil-water deficits at critical crop growth stages such as the seedling, flowering, and grain filling stages, and there is a risk of total crop failure (Reddy and Georgis, 1993; Engida, 2000). Up to 60% of the variability in maize yield is due to variability in growing season rainfall, which is a major concern for resource-poor and risk-averse farmers (Tesfaye and Walker, 2004; Kassie et al., 2013a, 2014). Next to climate risk, poor soil fertility is the single most limiting factor affecting maize production (Senay and

Verdin, 2003). In the region, these bio-physical constraints have largely exacerbated the prevailing poverty and food insecurity (Kassie et al., 2013a).

Despite the fact that farming systems are diverse, site specific, and influenced by the management, bio-physical, or socio-economic factors (Snapp et al., 2003; Tittonell et al., 2010), the agricultural research, development and extension (RD&E) services deliver fixed (instead of flexible) agronomic and technological recommendations such as blanket fertiliser and soil-water conservation practices in any given season regardless of a season's yield potential (Fujisaka et al., 1996a and b; Admassu et al., 2014). Such recommendations are known to increase crop productivity or profit in only average or good seasons (Colin and Crawford, 2000; Darnhofer et al., 2010). Instead, the vast majority of the risk-averse and resource-constrained smallholder farmers in semi-arid regions are more concerned about reducing the downside risk that would enable them to achieve the minimum livelihood in even the least favourable seasons (de Rouw, 2004). It is a fact that climate risk in the CRV region has presented the principal source of uncertainty in crop production, however, information on climate-induced yield variability as a consequence of recommended management strategies has been rarely available (Keating et al., 1991; Rötter and Van Keulen, 1997; Whitbread et al., 2010; Rao et al., 2011). Despite the fact that farming systems are diverse and variable within a locality and across locations within a region, the research and extension advisory services have only delivered 'prescription' uniform advice –rather than flexible and locally relevant information – regardless of the specific type of farming system (Colin and Crawford, 2000; Giller et al., 2009; Darnhofer et al., 2010; Goujard et al., 2011). As a result, there has been low adoption of technology that may otherwise be profitable or desirable to smallholders (Röling, 1990; Onduru et al., 2001; Snapp et al., 2003).

1.3. Purpose of the study

In the semiarid region of the CRV, farmers try to manage the uncertainty associated with rainfall variability by making field-level management decisions based on their long-term experience, knowledge and practical wisdom (Fujisaka et al., 1996a and b; Rao et al., 2011; Kassie et al., 2013a; Keshavarz and Karami, 2014). However, climate variability associated to inter- and intra-seasonal rainfall pattern have been the major causes for large fluctuations in crop production that contribute to prevailing drought and food insecurity of the region (Kassie et al., 2014). Traditional agronomic experiments, which are typically run for short seasons and limited sets of locations may be insufficient to meet these urgent needs (Jones et al., 2001) and they may also be ineffective in examining the long-term impact of the various agronomic management decision options under conditions of climate risk and uncertainty (Dixit et al., 2011; Stern and Cooper, 2011). For dryland farming systems with high seasonal and spatial variability, in particular, the inference from agronomic experimentations can be misleading if they are extrapolated to other seasons or locations beyond which the experiments are established for (Matthews et al., 2002; Saseendran et al., 2005; Zhang et al., 2005). In many countries of sub-Saharan Africa (SSA) including Ethiopia, for example, the use of 'blanket recommendations' at the broader scale of agro-ecology has quite often assumed the production system is homogenous (Schnier et al., 1997). However, many of the promoted recommendations fail to capture the variable bio-physical conditions of the local farming systems within the designated domain (Colin and Crawford, 2000; Smaling et al., 2002; Whitbread et al., 2010; Dixit et al., 2011; Kassie et al., 2013a). Moreover, the recommendations have largely overlooked the socio-economic factors that typifies smallholder farming systems (Ahmed et al., 1997; Snapp et al., 2003; Tittonell et al., 2010). As a result, most of the recommendations have not been adopted by the resource-poor smallholder farmers, particularly in the semi-arid regions of Africa (Croppenstedt et al., 2003; Snapp et al., 2003; Twomlow et. al., 2011).

In drylands where smallholder farms are highly diverse and variable in nature, the core element of research planning and strategies should ensure that recommendations are locally relevant and adaptable to a specific group of smallholder farmers (Fujisaka et al., 1996a; Gadgil et al., 2002; Whitbread et al., 2010; Rao et al., 2011; Twomlow et. al., 2011; Kassie et al., 2013a). A systems approach, which combines the capability of crop simulation modelling with a participatory research approach, enables researchers and extension advisors to formulate effective and site-specific recommendations that are compatible with the bio-physical and socio-economic environment of smallholder farming systems (Meinke et al., 2001; Kandji et al., 2006; Whitbread et al., 2010; Thornton et al., 2011; Kassie et al., 2013a). Better understanding and modelling of the complex factors and their interactions that drive the system dynamics or responses (e.g., crop yield, water productivity and N-use efficiency) can be considerably enhanced using credible and robust crop models (Hammer and Jordan, 2007). By examining model-based outcomes over many years, the consequences of various crop management decision options can be effectively explored in situations of risks associated with seasonal climate uncertainties in a more comprehensive manner than possible with conventional agronomic experimentation (Keating and McCown, 2001; Meinke et al., 2001). On the other hand, treating smallholder farmers as passive recipients of technologies has proven to be ineffective, and this leaves little room to actively engage participating farmers in dialogue to articulate about their problems and interest for possible improvement of practices in their actual management situations (Kumwenda et al., 1997; Snapp et al., 2002; Mulat and Teketel, 2003). Instead, farmer-researcher partnerships through engaging farmers in the research process of developing recommendations under their farming environment would allow deep insights into farmers' values, long-term aspirations, resource base and risk preference, and key socio-economic information which would assist researchers to efficiently and effectively target desirable and feasible technological interventions suited to specific socio-ecological niches (Ojiem et al., 2006). As a result, many smallholder farmers are more likely to adopt the promoted recommendations than the conventional top-down approach of 'blanket recommendations' (Ncube et al., 2007).

1.4. Significance and methodological overview of the study

In systems approaches, the methodological framework chosen can be used to effectively deal with complex and variable aspects of the farming system in an objective, practical, and scientific manner (Tow et al., 2011). Although agronomists tend to focus on the bio-physical system and discount the crucial human characteristics, systems-oriented methodologies enable agronomists to treat the subjective judgements of farmers from a human viewpoint and perspective with rigour (Checkland and Scholes, 1990). A systems approach is therefore a means to markedly enhance the design of agronomic recommendations that are locally applicable and socially feasible in the face of variable and uncertain climate. In this research project, a systems approach was achieved by linking a participatory research approach with model-assisted simulation modelling to effectively and efficiently study the interactions between the complex and variable bio-physical systems along with the human behaviour and activities.

A systems approach was followed in the study as a valuable methodological approach to ensure clear understanding of the complex and risk-prone characteristics of the smallholder maize-based systems, and to closely study the various factors that affect farmers' decisions in response to variable and uncertain climate scenarios. As farming systems are too complex to understand as a whole, a systems analysis was done by selecting and defining the appropriate level of scale to model. For this study, systems analysis was tailored at the field level, which is the most relevant scale to the decision maker. In this case, a maize-based system was the focus of the study because it is the dominant enterprise in the smallholder farming system at the study area. More specifically, maize is cultivated as the major staple food and contributes significantly to the livelihoods of the vast majority of smallholder farmers in the region (Biazin and Stroosnijder, 2012). The outcome of the analysis for the smallholder maize system as a consequence of the various management decision options were translated at farm scale in terms of improving crop productivity and food security.

In systems research, there are various participatory approaches to include local farmers' views and perspectives within the systems analysis framework (Lynam et al., 2007). For this study, the participatory diagnostic methods within RRAs were applied to understand views, knowledge and objectives of the targeted farming community at the study area by engaging them in individual interviews and focus groups discussion (FGDs). Once in-depth insight into farmers' views and perspectives was gained, better agronomic interventions were targeted that can help local farmers and their advisors to make informed decisions under variable and uncertain climate with which they have to cope. The systems approach was tailored to address the challenge of smallholder farmers through exploring opportunities, and consequently making locally relevant recommendations that are effective in improving maize productivity while reducing climate-induced risk. Given soil N in the CRV of Ethiopia is the most limiting factor constraining crop productivity at any given level of moisture availability (Biazin and Stroosnijder, 2012). In the region, good agronomic practices can improve efficiency of using the most limiting resources (i.e., water and N) in maize production systems. In the region, the majority of the risk-averse and resource-poor smallholder farmers might be encouraged to invest in N fertiliser at a small amount that can result in high returns to the fertiliser additions (Twomlow et al., 2010, 2011). At the study area, farmers' decisions are often limited by knowledge gaps on principles of basic agronomic practices (i.e., suitable sowing dates and cultivar choice), as well as by financial constraints and risk-averse attitude to invest in inputs such as fertiliser N that can significantly increase productivity in smallholder maize-based cropping systems. Therefore, simple agronomic recommendations that would require small additional fertiliser investment – within farmers' capacity (resource status or investment capacity) and capability (agronomic and technical skills, strategies and risk attitude) – have been sought to close the source of large yield gap of smallholder farmers in the region. Therefore, research of this kind need to focus on identifying simple and less-costly management opportunities for the majority under-performing smallholder farmers as a stepping-stone approach in raising yield substantially while reducing yield variability and risk (Twomlow et al., 2010; Roxburgh and Rodriguez, 2016). Through analysis of crop simulation, locally relevant management options were identified as feasible pathways to a step-wise sustainable intensification of smallholder maize production systems before farmers are simply expected to adopt complex technological innovations (e.g., conservation agriculture (CA) or integrated soil fertility management (ISFM) (Dimes et al., 2015). Cost- and knowledge-intensive technologies such as CA and ISFM that can present transformational change might be perceived by majority of farmers as too difficult, too risky, and even culturally unacceptable (Zeleke et al., 2004; Rodriguez et al., 2017). The methodological framework was therefore proposed to identify opportunities that farmers can easily adopt to increase their production level with minimum acceptable risk. In effect, farmers can enhance their capacity to invest in complex technological innovations in the future that help them to leap to a new efficiency frontier, which can potentially improve their crop productivity in the long-term while sustaining the basic natural resources (Keating et al., 2010).

The study used a number of research approaches. The first stage of the study involved farmer surveys or rapid rural appraisal (RRAs) for establishing better insights into farmers' perceptions of, and management responses to variable seasonal climate, and this was detailed in Chapter 3. The RRAs method was applied within this farming system research to effectively assess and understand the important aspects of the local farming systems and their decision-making in which farmers were actively involved in a participatory fashion to express their views and perspectives. The RRAs were conducted in three villages from two districts in the CRV of Ethiopia. Information from the interviews of 60 farmers and two FGDs within RRAs were combined to: (1) acquire better insights into farmers' understanding of production situations, such as farmers' perceptions and understanding of, and their agronomic responses to climate variability and risk; (2) examine how this influenced the way they articulated their situational constraints, which was considered as an essential step in the research process for identifying farmers' needs for planning agronomic research and targeting feasible interventions that can be adapted to the local bio-physical and socio-economic conditions of the farming systems. First, farmers' perceptions on climate variability were investigated and then their subjective assessments were compared with the objective assessment of observed historical climate observations. Farmers' estimation of frequency of favourable and unfavourable seasons and their criteria to classify different seasons were highlighted. Then, farmer's key agronomic decisions, which are important to cope with the current variable climate, are explained. In dryland environments including the CRV region of Ethiopia, simulation modelling was proposed as an effective research tool in providing a more thorough and objective assessment about the nature of the farming system under investigation. The effect of climate-induced risk on maize yield as a consequence of a spectrum of agronomic management options were evaluated in consideration of the historical seasonal variability (Hansen and Jones, 2000; Keating and McCown, 2001; Meinke et al., 2001; Keating et al., 2003; Hansen, 2005; Cooper et al., 2008; Moeller et al., 2008).

Even though crop models are a feasible and sound research and decision tool, they are rarely used in SSA countries largely due to a lack of quality and reliable database, among many other reasons (Bontkes et al., 2001; Bontkes and Wopereis, 2003). As a rule, crop models ought to be parameterised and evaluated under the local conditions of the study area before they are practically applied for conducting long-term simulation scenarios to explore various management options, and subsequently recommend feasible interventions for the local farming systems. In Ethiopia, the lack of a detailed and comprehensive database is one of the limitations for reliable use of crop models for *ex-ante* evaluation of management opportunities, and for identifying management decision options that can successfully fit into the conditions of resource-limited and risk-averse farmers in the study region (Kassie et al., 2014; Getnet et al., 2016). The Agricultural Production Systems sIMulator known as APSIM (Keating et al., 2003) was used because it is a robust crop model that has been extensively tested and used to explore a range of management decision options to identify opportunities for possible change in management practices (Keating et al., 2000; Shamudzarira et al., 2000; Dimes et al., 2002; Shamudzarira and Robertson 2002; Robertson et al., 2005; Whitbread et al., 2010). The APSIM model has been applied successfully in exploring a range of strategies for more efficient production, improved risk management, crop adaptation, and sustainable production (e.g., Keating et al., 2003; Van Ittersum et al., 2013).

For this study, all the relevant cultivar- and soil-related parameters for running and evaluating the APSIM model were determined from a field experiment conducted in 2012 at Melkassa, the CRV of Ethiopia (Chapter 4). The field experiment was setup with a three-factor split plot design in three replications as follows: two sowing dates as the main-plot treatment and two medium-maturing maize cultivars and two rates of N fertiliser as sub-plots treatment. APSIM was parameterised using weather data from the Melkassa meteorological station for parameterising the common and locally adapted medium-maturing maize cultivar (cv. *Melkassa-2)* and with soil characteristics typical of the soil type in the CRV region (Chapter 5). Suitable datasets were collected on crop phenology, growth, grain and biomass yields (i.e., to derive cultivar parameters of cv. *Melkassa-2*), data on soil physical and chemical properties (e.g., soil water and N parameters), and detailed information on soil and crop management (e.g., sowing time, fertiliser rate and timing). The APSIM model version 7.5, including Maize, SoilWat (soil water), SoilN (soil N), Surface Organic Matter and Manager Modules, were linked for simulating the complex climate-soil-crop systems. To test model performance, the parameterised APSIM was evaluated using independent datasets that were collected from various field experiments at Melkassa in the years between 2006 and 2012. Using the six year datasets, the model was tested for its capability in reproducing the observed variations in maize yield as affected by climate and management factors. In model evaluation, the performance of APSIM was assessed by comparing the closeness or deviation of the relationships between observed and simulated values using both graphical and numerical methods (Jamieson et al., 1991; Mitchell, 1997; Soler et al., 2007). The statistical indicators to assess model performance included: the absolute root mean square error (RMSE) and normalised or relative RMSE (n-RMSE calculated as RMSE as a percentage of the observed average), and the coefficient of determination (r^2) of the regression of observed against simulated values through the best fitted line. Low RMSE and n-RMSE (of the same, or less, order of magnitude as experimental standard deviations and as the coefficient of variance) and high r^2 values indicate good agreement between model outputs and observed values. The parameterised model performance was furthermore evaluated against farmers' experience using yield estimates provided by the farmers from their historical observations for the bad, average and good yields at the study area of Melkassa.

The parameterised APSIM model was then configured to run long-term simulations according to the management requirements of each scenario in question (Chapter 6). In the simulation, three key agronomic decisions (sowing time, cultivar choice and rates of N fertiliser), which were identified by participating farmers as important agronomic factors (Chapter 3), were considered. In the long-term simulation study, each season was modelled independently of other seasons with re-initialisation of input parameters at the date of sowing when the sowing criteria was fulfilled for each sowing window. Farmers' level of achievement to fulfil their objectives when they are employing different agronomic approaches can be quantified using various indicators of system attributes such as economic profitability, productivity and food security (López-Ridaura, 2006). In this study, crop yields were used as an indicator of the objective at the farm level in achieving household food security.

Different management strategies were explored by running simulation models using long-term daily weather data of the Adamitulu and Melkassa meteorological stations for a period of 34 and 39 years, respectively. As a result, the management strategies of the local farmers were evaluated along with the recommended management strategies from research and extension services. The APSIM model was also configured to simulate maize yields as modified by the factorial combinations of key agronomic factors: sowing window (early, normal, and late sowing dates), cultivar type (early-, medium-, and late-maturing cultivars), and N fertiliser rates (0 kg N ha^{-1} (N0), 25 kg N ha^{-1} (N25), and 50 kg N ha^{-1} (N50)). Altogether, there were 54 management scenarios to analyse where a number of different management decision options were simulated in order to understand the potential for smallholders if better management was adopted. The simulated grain yields were analysed using an unbalanced analysis of variance to test if there were differences and/or interactions among the simulated agronomic factors. For resource-poor and risk-averse smallholder farmers, climate-induced yield variability and risk are often as important as the long-term average maize yield. Long-term simulation scenarios were analysed and assessed for seasonal variation in maize yields and for risk of crop failure, along with the risk of falling short of "threshold" yield levels that a typical farmer in the study region would expect to achieve in any given year. From the simulation output, production risk of the various combinations of agronomic factors was analysed by comparison of probabilistic estimates of yield for a range of combinations of management decision options (sowing time, cultivar maturity-type and rates of N fertiliser). As an indicator of production risk or inter-seasonal variation in maize yields associated with each agronomic management and investment in N fertiliser, the value of coefficient of variation (CV, %) was assessed to quantify randomness relative to the long-term average yield of maize (Hardaker et al., 2004a). Therefore, risk to maize production was assessed in terms of factors that contributed most to yield variability. The Kolmogorov–Smirnov test was computed for pair-wise comparisons of yield distributions of the recommended agronomic strategy against the conservative or baseline strategy of the local farmers. The local practices of the typical farmers, who are risk-averse and unwilling to apply N fertiliser, were represented by the scenario called 'baseline strategy'. The local practices of the farmers, who are applied a modest rate of N fertiliser, were represented by the scenario called ‘conservative strategy’. The analyses of the modelled scenario had not been subjected to the subsequent farmers’ evaluation due to time constraints. In the subsequent chapters of the thesis, the importance of linking participatory research and simulation modelling approach that is effective in engaging farmers to evaluate scenario outputs have generally been discussed in relation to its implications for climatic risk management and pertinent issues for future research.

1.5. Main aim and objectives of the study

The overall aim of this thesis is to identify potential management options that could improve the productivity of crops and reduce risk associated with fluctuations in crop yields under smallholder maize systems in the semi-arid Central Rift Valley of Ethiopia. The specific objectives are to:

1. Acquire better insights into farmers’ perceptions and understanding of, and their response to, climate variability.
2. Investigate the key agronomic management strategies currently employed by farmers in that area and understand their interest in and attitude towards various agronomic factors in the face of climate risk and uncertainty.
3. Determine the effect of contrasting sowing dates and N fertiliser application rates on growth, development and yield, along with water productivity of maize crop.
4. Obtain the essential inputs and parameter settings to apply a simulation model of a maize production system (APSIM).
5. Evaluate the ability of APSIM to realistically simulate maize systems in the study area; the CRV of Ethiopia.
6. Apply the APSIM for evaluating alternative management strategies along with the typical farmers’ local management practices.

1.6. Research hypotheses

The research question at the core of this work were summarised as:

Is a systems approach that integrates a participatory approach through engaging farmers in interviews and discussions combined with the capability of simulation and modelling effective for targeting agronomic interventions that are locally relevant for smallholder farming systems to bring incremental change in crop productivity under climate risk and uncertainty?
Is a systems approach effective for moving towards more resilient and productive smallholder farming systems through targeting feasible agronomic strategies that can ensure a feasible pathway to the step-wise sustainable intensification of the maize production system in the semi-arid region of CRV Ethiopia?

To answer these questions, the thesis tests the following hypotheses:

1. The various management decisions that farmers are using to deal with the impact of climate variability is dependent on farmers' perceptions of climate variability and their criteria to describe a season of one year to another year.
2. Farmers' management practices that are guided by their heuristics (local knowledge and experience) are inadequate to deal with the problem of existing climate variability.
3. Maize growth, development and yield, as well as water productivity of maize, can be significantly affected by varying sowing dates and contrasting rates of N fertiliser. Under this hypothesis, the collected data were used to parameterise and evaluate the APSIM model in simulating key crop attributes (crop growth, development and yield) and soil processes (soil water dynamics) as affected by interacting effects of the local environment and management factors.
4. The APSIM model can realistically simulate the maize production system under the local conditions of the study area, and hence it can be reliably applied to evaluate performance of the smallholder maize systems that are affected by varying management regimes, including local farmers' management practices.
5. Fixed agronomic recommendations from research and extension services are ineffective to manage climate variability and risk since they do not account for the varying seasonal

prospects of the local area, nor do they conform to farmers' production objectives, resource constraints, and risk-aversion behaviour.

6. APSIM could be applied as an effective tool for long-term simulation scenarios for quantifying production levels and risks associated with current and alternative management strategies.

7. Model-aided assessments can assist in identifying feasible pathways for targeting locally relevant agronomic interventions that are adaptable to resource-constrained and risk-averse smallholder farmers who are operating under variable and uncertain climate.

1.7. Outcomes of the study

The main outcomes from this research include:

1. Better insight into farmer perceptions of climate variability, including their common characteristics or differences within or between the farming communities at the study area.
2. Identification of some of the knowledge gaps regarding farmers' risk attitude and responses towards climate variability that are useful to design successful agronomic strategies, which are well-targeted according to farmers' production objectives, aspirations and risk preferences.
3. Production of quality and comprehensive datasets valuable to parameterise and evaluate APSIM for modelling maize-based system in the semi-arid region of the CRV Ethiopia.
4. Better information on the risk profile of management scenarios by using model-assisted simulations and long-term sequences of climatic data that allowed quantifying probabilistic estimates of maize yield for a suit of management options, including local farmers practice and current recommendations from local extension services.
5. Provision of good insight into the opportunities associated with the various management decision options in situations of risk associated with seasonal climate uncertainties.
6. Potential management opportunities for local smallholder farmers if they are adopting them for the maize-based cropping system in the region.

1.8. Outline of the thesis

To address the main issues and objectives of the study systematically, the thesis is organised into seven chapters. A brief summary of each chapter is outlined below.

Chapter 1 sets the scene and describes the background information that inspired this study. It presents a problem statement and the purpose of the study. This chapter describes the scope and context of which the study was done, along with significance of the study and a general overview of the methodological approach. The chapter is also the platform to outline the overall aim, the specific objectives and the major research questions along with the hypotheses that were tested as detailed in the follow-up chapters. Finally, the chapter presents outcomes of the study, followed by an overview of the thesis structure.

Chapter 2 presents a comprehensive review of relevant literature related to the aims of the research, and outcomes of the literature review will form the basis of the specific research hypotheses detailed for the experimental chapters that follow. The objectives of the review chapter are to review (i) how small scale farmers operating in dryland environments (e.g., developing countries in tropics and subtropics) manage climate-related risks; (ii) how farmers respond globally to climate variability and climate changes in similar socio-economic and climatic environments and relating these responses to an Ethiopian context by outlining existing barriers and constraints; (iii) key concepts and principles underlying 'systems approaches' in the context of farming; (iv) past and current advancements in crop simulation models and application of modelling and simulation approaches in farming systems research; (v) participatory approaches within farming systems research; (vi) the relevance of modelling and simulation within participatory research to manage climate risk; and (vii) the value, challenges, and future prospects of adopting participatory approaches and simulation-based research and extension.

Chapter 3 discusses the main results from the RRAs, including information based on focus groups, questionnaire surveys, and reviews of secondary sources. It examines farmers' perception and knowledge of climate variability (e.g., rainfall, temperature, and drought) and assesses how their understanding of climate variability translates into farm management decisions and actions.

The major discussion in Chapter 4 is about field observations and measurements as important input datasets for model parameterisation and evaluation. Here the outline of the field experimental design and its layout, crop management, time of sowing, cultivar type and fertiliser treatments, as well as sampling details and measurements, for the collection of both in-season and end-season measurements for the key crop and soil processes is described. The data collected from the maize field experiment in Chapter 4 were used for the purpose of obtaining the essential parameter settings for use in APSIM.

Chapter 5 deals with parameterisation and evaluation of the APSIM model. The parameterised and evaluated APSIM model was configured to simulate maize yields as modified by the agronomic factors in question (different sowing time and rates of N fertiliser), using long-term sequences of climatic data and local maize cultivar and soil information.

Chapter 6 addresses the application of APSIM for simulating what might happen when agronomic practices are changed in situations to deal with risks associated with seasonal climate uncertainties. The long-term simulations for this specific situation were tested for the Melkassa and Adamitulu locations in the CRV region. In the simulations, the likely risk as a consequence of management decision options were explored to provide probabilistic estimates of yield for varying combinations of agronomic factors, such as sowing time, cultivar type and rates of N fertiliser. The output from the scenario analyses were discussed by comparing various agronomic management approaches, including the local practices of the farmers and agronomic recommendations from research/extension services along with various combinations of alternative agronomic management options. The long-term risk-return performances of a wide range of potential management scenarios were explored.

Chapter 7 presents the main conclusions from the study. It provides methodological outlooks and discusses the major findings and limitations of the study and provides recommendations leading to avenues for further research both to clarify some specific aspects and to apply the presented findings in practice. Full details of all references used within various chapters are given in the references section. The focus groups questions and the interview questionnaire used in the farmer survey (Chapter 3) are presented in the Appendix.

Chapter 2 Literature Review

Abstract

In farming systems with high seasonal, spatial and socio-economic variability, systems approach that recognises farms as functional entities comprising bio-physical, technological and human factors in analyses is vital in formulating possible solutions to answer critical problems for smallholder farmers. A key component of many farming systems are the crops. A wide variety of crop simulation models have been developed to enhance our understanding of the key drivers of crop productivity under a range of management practices, soil types, and climates. Recent advances in crop simulation models have increased their relevance and credibility for simulating increasingly complex farming scenarios, including constraints experienced by smallholder farmers. However, the benefits of crop simulation models to directly assist famers with practical management decisions have not been fully realised, in part, due to the limited knowledge transfer and communication between farmers and researchers. To improve knowledge transfer and farming practices, participatory research (PR) approaches have been applied whereby it is proposed that the relevance of computer-based modelling could be improved by directly involving farmers in the design and analysis of simulation scenarios within PR. This approach has been used to gain insights into complex systems, supporting co-learning and assisting farmers with decision-making. By combining both the cropping system modelling and PR, it would be possible to develop a more robust methodological framework to study scenarios unique to resource-poor farmers of Africa. This review examines how systems approaches can assist in understanding farming systems and develop planning options for farmers constrained by resource availability and climate variability. The objectives of the review are to summarise the information of farming systems, past and current advancements in cropping system models and simulation modelling approaches for designing various crop management systems. The historical perspective of farming systems and PR is also examined and future opportunities for advancing participatory modelling approaches in farming systems research, extension, and development efforts in developing countries are proposed.

2.1. Introduction

In many developing countries, approximately two-thirds of the population depend either directly or indirectly on agriculture for their livelihood (Hansen, 2005; Fischer et al., 2014). A principal source of risk affecting the long-term economic viability of agricultural industries and smallholder farms in many developing countries is climate variability (Thomas et al., 2007; Cooper et al., 2008; Conway and Schipper, 2011). The issue of climate variability is particularly worse for smallholder farmers operating in dryland environments (Devereux, 2001; FAO, 2006, 2008). In this context, 'smallholder farmers' are defined as farmers who manage farms that are usually no bigger than 2 ha in size and rely on household labour to sell a portion of their produce for cash (Akram-Lodhi and Kay, 2010). Consequently, farming in these regions is a risky enterprise, especially for resource-poor farmers (Meinke et al., 2001; Cooper et al., 2008; Thornton et al., 2011).

Drylands cover 41% of the world's land surface. They also support 35% of the global population, the majority of whom are the rural poor (Safriel and Adeel, 2008). Dryland farming is practiced in semi-arid and dry sub-humid regions where crop production is limited by moisture availability for part of the year (Dregne et al., 2006; Stewart et al., 2006). Dryland regions are classified using the number of growing days (FAO, 2000) and an aridity index (UNEP, 1992). According to the FAO (2000), drylands are those areas with a growing season length of 1–179 days, while the UNEP defines drylands as areas characterised by a ratio of annual precipitation to potential evapotranspiration ranging between 0.03 to 0.5. Under these definitions, approximately 60–72% of dryland regions are located in developing countries (Safriel et al., 2005). For any farming system, sustainability (environmental, economic and social) is the ultimate goal (Stoneham et al., 2003; Seymour and Wickes, 2011) and in these dryland regions, rainfall variability is a constant and dominant source of livelihood risk in smallholder farming systems (Cooper et al., 2008; Thornton et al., 2011).

The wide range and variability of rainfall in dryland environments is a major challenge for conducting agricultural research and devising agronomic recommendations for these systems (Dixit et al., 2011; Stern and Cooper, 2011). Farmers are looking for options that take climate uncertainty into account rather than those developed for 'on average' conditions. A risk analysis of the trade-offs between increasing yield gain or profit and increasing risk may be helpful in addressing this concern (Cacho et al., 1999; Woodward et al., 2008). However, neither the extension advisory services nor the extension publications have seriously taken into consideration the various factors that may influence the long-term impact of agronomic recommendations including seasonal variation, risk of any endorsed technology, resource constraints, and the risk attitude profiles of different smallholder farmers (Whitbread et al., 2010). Without knowledge of the effects of climate variability on the performance of recommended technologies, farmers cannot be properly advised by research and extension services regarding the possible climate risks they may face (Dixit et al., 2011). Agronomic recommendations need to be flexible and take into account resource constraints, farmers' objectives, and the risk levels farmers find acceptable so they are better able to manage climate risk and uncertainty (Fujisaka et al., 1996a and b; Cooper et al., 2008; Kassie et al., 2013a).

Climate-related risks have been analysed for a range of crop, soil and water management options practiced in Africa (Rötter and Dreiser, 1994; Thornton et al., 1995; Dixit et al., 2011; Kassie et al., 2014). Carberry et al. (2004) used a participatory approach combined with computer-based modelling of a smallholder maize system in Zimbabwe to identify risks associated with various crop management technologies. By coupling a participatory approach and modelling capability, Carberry et al. found that farmers were interested in applying fertiliser at greatly reduced application rates, namely a micro-dose of nitrogen (N) application (i.e., 10 kg N ha^{-1}), more tailored to the smallholders' climatic and socio-economic conditions, which could still markedly increase the mean yields of their maize. Simulation modelling demonstrated that this fertiliser management option could potentially increase crop yields, which was later confirmed in field studies (Twomlow et al., 2010). The success of the micro-dosing technology was attributed to its bottom-up approach in technology transfer. That is, farmers were consulted and involved in the decision-making process during the development and promotion of the technological packages (Anandajayasekeram et al., 2008). The results have provided strong evidence that N micro-dosing has the potential for broad-scale impact on food security for a significant number of resource-poor farmers in dryland areas (Twomlow et al., 2010, 2011).

However, much of the current technology transfer has been based on a top-down approach of technology transfer whereby an agricultural message has been designed and developed by research scientists, with limited input from the ultimate users of the technologies (i.e., the farmers). This top-down approach has been criticised for its poor understanding of the wide diversity and heterogeneity of farmers, and the environments in which they operate (Sands, 1986; Simmonds, 1986), as well as the opportunities and constraints the farmers may face (Anandajayasekeram, 2008). Examples include the introduction of fertiliser recommendations (Dimes, 2011), hybrid seed technology (Nkonya et al., 1997; Zavale et al., 2005), and soil-moisture conservation practices (Mupangwa et al., 2006; Tenywa and Bekunda, 2009). These technologies have provided some improvements but only under very specific conditions, i.e., for homogeneous commercial farm units and under stable economic conditions (Jiggins, 1993; Packham, 2011). Darnhofer et al. (2010) noted that farmers failed to adopt technological packages especially in marginal environments. For example, the poor adoption of solutions developed with an 'engineering mindset' is exemplified by the apparent lack of interest to follow the recommended rates of fertiliser in semi-arid Africa (Croppenstedt et al., 2003; Snapp et al., 2003; Twomlow et. al., 2011).

Developing management practices and technological options that take into account the local context of farming communities is necessary to enhance the adoption of more sustainable and productive farming practices (Okali et al., 1994; RÖtter and Van Keulen, 1997; Snapp et al., 2003; Cooper and Coe, 2011). That is, the recommended technologies should include adequate information on the risks and returns of the proposed technologies so the farmers can make informed decisions depending on their resource endowment and ability to take risk (Rao et al., 2011). As the farmers' different production goals and attitudes towards risk are not well accounted for, local recommendations are often unsuitable for smallholder farmers in many sub-Sahran Africa (SSA) countries (Dimes, 2011; Twomlow et al., 2011). As a result, the challenge of achieving food security in these countries has remained unachievable (RÖtter and Van Keulen, 1997). The problem is compounded by the high population growth of most countries in the region, aggravating future food security concerns (FAO, 2009). Paying close attention to the farmers' perspectives by tailoring the recommendations from research and extension services to offer practical solutions to a spectrum of farmers in making informed decisions about technology adoption should help alleviate concerns regarding food security (Dimes, 2011).

2.2. Systems Approaches in Farming System Research

2.2.1. What is a Farming System?

A system refers to a set of interacting components, as influenced by internal and external factors, that are grouped together to study some aspect of the world (Jones and Luyten, 1998; Wallach et al., 2014). Because of its complexity, it is always necessary to separate a system into its components and sub-systems (Tow et al., 2011). For analytical purposes, a system is conceptually separated from the rest of the 'environment', by a 'system boundary' (Kelly and Bywater, 2005; Tow et al., 2011). The environment of a system includes everything except the components of the system that may be described as factors that directly influence the behaviour of components in the system but are not affected by them (Rabbinge et al., 1994; Wallach et al., 2014). An example is a cropping system constituting crop and soil components, which interact with the weather conditions and the crop management. Systems approaches start with the definition of the system to be studied and this involves development and use of the model to study the defined system.

Definitions of the term 'farm' vary greatly depending on the perspectives of the analyst, which may include economists and agronomists (Keating and McCown, 2001). Using a systems approach, a farm is generally defined by two interacting sub-systems. Firstly, the production sub-system, which includes the bio-physical and technological domain, and has been well-documented in the literature (Hunt and Boote, 1998; McCown and Parton, 2006; Castellazzi et al., 2008). The management sub-system, includes the human domain with the management histories, policies, and processes at different spatial scales (McCown, 2001; Le Gal et al., 2010).

The management sub-system, especially the human component has been less emphasised (McCown, 2001; Darnhofer et al., 2010) and the inclusion of a management sub-system reflects a shift of the system boundary (McCown, 2001). In contrast, Le Gal et al. (2010) defined a farm as having three sub-systems; the bio-physical, technical and the decisional sub-systems. The last two sub-systems fall within the management sub-system as defined by McCown (2001). Ongoing monitoring of the production sub-system by the farmer informs decision-making processes and management adjustments are undertaken accordingly to achieve the purpose of the management sub-system (McCown, 2001).

The management sub-system is characterised by both internal and external factors (Darnhofer et al., 2010). Internal factors refer to bio-physical resources such as plants, animals, and soil while external factors include climate, farm inputs such as seed, fertiliser and labour, as well as market conditions and legal frameworks such as credit accessibility, insurance, and government policies. Management decisions are grouped into three main categories; operational, tactical, and strategic (McCown, 2001; Le Gal et al., 2011; Tow et al., 2011). Decision makers implement operational decisions on a daily/weekly basis (e.g., crop planting and fertiliser application). Tactical decisions are made at any time before or during a season in response to unpredictable factors such as changes in climate and market. Strategic decisions are made over several years with the aim of creating a sustainable farm (Cooper and Coe, 2011; Le Gal et al., 2011). All these management decisions are influenced by regional heterogeneity, which also needs to be considered when developing management options for local conditions such as spatial variation in soil type (Hansen and Jones, 2000; Snapp et al., 2003) and potential yield difference across regions (Xiong et al., 2008; Ncube et al., 2010).

2.2.2. Farming Systems Research in Developing Countries

Farming systems research in Africa has been based on an earlier model of a systems approach that was developed in the 1970s in response to the failures of positivist-reductionist research to ‘get agriculture moving’ (Davidson, 1987). The original purpose of farming systems research was to improve farm productivity (Dixon et al., 2001). However, after the failures of the Green Revolution, which had restricted aims of improving productivity in marginal agro-ecosystems of Africa, this vision was broadened in the early 1980s to achieve other goals including sustainability, i.e., improved productivity integrated with social equity and protection of natural resources (Klerkx et al., 2012). Rather than promoting commodity-based technologies (usually a single technical component and, at best, two or three), farming systems research was based on an interdisciplinary holistic framework for planning research and extension activities to address farmer’s problems and constraints (Flora et al., 2000). From the mid-1980s, research institutions and non-governmental organisations that were involved in developing and testing new technology criticised farming systems research for being too linear and prescriptive (Okali et al., 1994). These criticisms led to improvements in farming systems research methods including the application of technology-user assessments, on-farm trials and farmer participation such that technological developments were more flexible and responsive to priority constraints faced by smallholder farmers (Martin and Sherington, 1997; Collinson, 2000). In the 1990s, farming systems research was greatly improved by the inclusion of participatory research, and this represented a new approach of not just doing research for farmers, but also working with farmers (Darnhofer et al., 2010).

2.2.3. Participatory Research

Social scientists in the 1980s proposed the idea of involving farmers more systematically and actively in the research process to take advantage of the farmers' own skills for innovation (Sutherland, 1998). In the 1990s, with an increasing appreciation of the complexities and uncertainties of farming systems, there was recognition that formal science did not sufficiently address a number of issues, including an inability to take into account the role of the socio-political climate and local contexts of farmers' choices, as well as farmer's subjectivities (Darnhofer et al., 2012). In response, a new approach termed 'participatory research' (PR) (Sutherland, 1998; Ison, 2008; Darnhofer et al., 2012) was developed that utilises a group of methods and/or tools for facilitating the active involvement of different stakeholders (e.g., farmers, extension people) in the research process (Chambers, 1989; Röling and Jiggins, 1998; Sutherland, 1998).

The aim of PR is to improve farmer-researcher interactions, which allow for a better understanding of farmers' needs, criteria and perceptions (Lisson et al., 2010; Ortiz et al., 2011). Furthermore, PR encourages farmers to express what they need to know, particularly their perceived problems, and possibilities for developing improved practices (e.g., McCown, 2001; McCown and Patron, 2006). Participatory methods can be applied to different groups in a community, or different regions, in order to cater for divergent needs, opinions and experiences in each category (Pain and Francis, 2003; Bacic et al., 2006). In other words, it is advocated as a means of offering a 'basket of options' for individual households to select recommended technologies that best suit them (Chambers, 1989). The learning outcomes also come from combining different types of knowledge, e.g., experiential and experimental knowledge (Scoones and Thompson, 1994). This could be especially important, for example, when working with poor farmers, as they usually do not have the required organisation skills and influence to represent themselves in mixed groups (Sutherland, 1998).

The participatory approach has been advocated as a powerful tool for assisting farmers make informed decisions on selected technologies (Chambers, 1989; Heinrich, 1993). The engagement of relevant stakeholders in PR contributes to increased effectiveness by improving both the quality of decision-making and demonstrating legitimacy through greater transparency and the pursuit of legitimate self-interests (Newig, 2007). The need for participatory approaches to support research for technological change has been broadly accepted (Hall and Kidd, 1978; Bentley, 1994; Pain and Francis, 2003). In particular, smallholder farmers are more likely to accept the results and recommendations of research if they have been engaged in developing the recommendations under their farming environment (Twomlow et al., 2011). Even though it is widely accepted among researchers and development specialists that farmer-driven processes can spur rapid widespread adoption and adaptation, many researchers and development specialists still fail to understand or take into full account farmers' real priorities (Kanyama-Phiri et al., 2000; Douthwaite et al., 2003). According to Bentley (1994), establishing an unbiased and clear means of communication between scientists and farmers is difficult mainly due to their socio-economic distance and different interests between the two groups. Hence, having clear objectives in mind, such as where to work, who to work with, and how to work with them have been recognised as critical decisions that can strongly affect the success of a participatory approach (Bellon, 2001). On the other hand, PR has also been criticised as a 'slow' process, since all meetings must be planned ahead to match the schedules of all the member of the target groups (e.g., farmers, extension persons), and enough time must be allocated for each activity in the program, which may not always fit the scientists' agenda (Branney et al., 2000).

Participatory research methods can be classified using four types of relationships between researchers and farmers: contract, consultative, collaborative, and collegiate (Biggs, 1988). In the contract relationship, there is a contractual agreement with farmers to take part in a project in which the participating farmers are not engaged in the research process other than providing their land and services. The consultative relationship is defined as a mode of participation in which farmers are asked to provide information and researchers develop possible solutions. The collaborative relationship is characterised by a small degree of farmer engagement in the research process and working together with researchers. The collegiate relationship allows farmers and researchers to work together as colleagues for facilitating mutual learning where farmers have control over the process. The most frequently observed form of participation is consultative where farmer participation tends towards the 'passive' as opposed to the ‘active’ end of participation typologies such as collaborative and/or collegiate participation where farmers are empowered (Pretty, 1995). MacMillan and Benton (2014) suggested that farmers are more likely to adopt new practices when farmers produce the knowledge, so clearly there is a need to involve farmers as much as possible in the research process. Ortiz et al. (2011) pointed out that the incentives and disincentives perceived by individuals and organisations are the motivation for promoting and using PR. In a study by Rusike et al. (2006), they asked farmers about what worked well and what did not for each stage of the participatory process, and summarised the best practices to be (i) engaging farmers in a genuine dialogue, (ii) addressing their concerns, and (iii) presenting new technologies through learning-by-doing and learning-by-using approaches.

Advancing joint learning is a central tenet of participatory approaches (Carberry et al., 2002; McCown and Parton, 2006; McCown et al., 2009). However, the question of how to harness the knowledge and experiences of researchers and farmers for the generation of new knowledge has been an area of contention (Hoffman et al., 2007). Participatory action research (PAR) is promoted as an avenue for researchers and their clients to work together collaboratively so that they can co-generate knowledge through ongoing communicative processes and joint implementation of research findings in their practical context (Ison, 2008; Mackenzie et al., 2012). The method fuses action research (multiple cycles of inquiry, action and reflection/revision) with the participatory approach (researchers collaboratively engage in the project implementation with the stakeholders) (O’Brien, 1998; McCown, 2001). The output of PAR may lead to social action and reflections for understanding new concepts and/or open up new areas of inquiry (McCown, 2001). This approach recognises that science alone cannot address the challenges facing agricultural systems, however, meaningful participation of relevant stakeholders is required (Carberry, 2001).

2.2.4. Why Use Systems Approaches?

Natural scientists are positivist, and generally consider knowledge as being independent of context and see the positivism perspective as sufficient in understanding realities of social life (Douthwaite et al., 2003). However, the implicit positivist approach cannot sufficiently understand the socially constructed nature of reality through the formal scientific approach—using empirical research to establish causal-effect relationships between variables (Darnhofer et al., 2012). Much of the research in agriculture has used a positivist ‘reductionist approach’

(Bawden, 1995). A reductionist approach deconstructs a complex system into its components and focuses on the interconnectedness of these components in a linear manner (Kalaugher et al., 2013). The reductionist approach has been criticised for its failure to assist smallholder farmers in marginal environments (Norman, 2000; Darnhofer et al., 2010) largely due to its inability to consider interactions in complex systems (e.g., crop and farming systems) in a non-linear manner (Kalaugher et al., 2013). In response to this limitation, researchers have sought a new approach to take into account the complexity of the farming system, i.e., systems approaches (Bawden et al., 1985; Van Eijk, 2000). Systems approaches have been applied to farm management since the 1970s (Gilbert et al., 1980) and integrate different disciplines and incorporate multiple perspectives (Kropff et al., 2001). For example, systems approaches can combine knowledge of agro-ecosystems, system theory and modelling techniques to provide a framework for analysing multiple variables and complex interactions that are characteristic of small-scale farming systems (Simmonds, 1986; Kropff et al., 2001). Therefore, a systems approach is ideal for analysing production systems characterised by dynamic complex behaviours (e.g., non-linear interactions) (Kalaugher et al., 2013).

The integrated nature of systems approaches contrasts strongly with the highly reductionist approach taken by early agricultural scientists (Collinson, 2000). A multi-disciplinary approach provides a more holistic framework of developing alternative solutions to farming issues (Rodriguez and Sadras, 2011), and recognises the contributions of researchers, modellers and practitioners (Hammer et al., 1998, 2002). Progress in systems approaches was initially impeded by difficulties that arose from differences in disciplinary perspectives, for example, the clash between the positivist perspectives of natural scientists and the constructive paradigms of social scientists (Van Eijek, 2000; Darnhofer et al., 2012). Darnhofer et al. (2012) suggested that understanding human behaviour using a positivist approach may be flawed because human behaviour cannot easily be explained using scientific cause-effect relationships. Darnhofer et al. (2012) also recognised the limitations of the constructive paradigms, as this approach relied heavily on the farmer’s reality, which may be skewed.

Darnhofer et al. (2012) suggested an integration of the positivist and constructivist paradigms by exploring the complexity of interactions within the ‘hard’ system (the researcher’s definition of the farming system, i.e., biological and technological components) and within the ‘soft’ system (the farmer’s definition of a farming system, which is based on their experiences and perceptions). Farmers view their farming system in their own right as 'constructs of their mind' and as such, they are influenced by their own personal preferences, cultural norms, and by the behaviour of their neighbours (Chambers, 1994). It is important to consider these factors because they drive farmers' choices, constraints, and goals as determined by the constructed perceptions (Darnhofer et al., 2012). However, the knowledge developed by farmers is often different in nature to that developed by professional researchers (Kalaugher et al., 2013). The integration of the hard and soft systems has greatly improved systems approaches, enabling researchers to capture the interactions between the 'material-technical' aspects of the hard system and the subjective perceptions, values and preferences of the soft system (Kay and Bawden, 1996; McCown and Patron, 2006; Klerkx et al., 2012; McCown, 2012; Milestad et al., 2012).

Participatory approaches have facilitated the integration of farmers' knowledge with scientific knowledge, thus fuelling reciprocal learning processes (Darnhofer et al., 2012) and the shift in systems approach research has greatly assisted in bridging the gap between formal science and the real world for developing practical innovation (King, 2000). A key element in the effectiveness of any integrated participatory research is the recognition of the validity of different epistemologies or conceptualisation of knowledge (Darnhofer et al., 2012). Conceptualising systems as constructs helped people to appreciate the same system with its elements and its context in different ways. Unlike research situations co-constructed by the researcher, conceptualising systems as constructs of farmers' unique experiential history is important as people appreciate the same system, with its elements and its context in different ways. Engaging farmers as ′experts′ instead of ′users′ in social learning processes help to better understand and capture the different models of a system (i.e., constructions of a situation) as people appreciate the same system, with its elements and its context in different ways according to their experiences, local conditions and purposes (Darnhofer et al., 2012). Both traditional and participatory approaches generally involve time-consuming and costly experimental work to arrive at the technology options that are most likely to work. Because of the resources involved, these experiments are undertaken at a restricted number of locations over limited periods. Extrapolation of the results and their interpretation in the context of farmer-first approaches is a problem.

Models are useful tools in biology to bridge the dialectic between reductionism and holism (Hammer, 1998) since they can explain phenomena at one level of biological organisation, e.g., a crop, by integrating responses at the immediately lower level, e.g., a plant (de Wit, 1970). Systems approaches provide a framework for interdisciplinary research (Wallach et al., 2014) and within this approach models are valuable research tools for integrating interdisciplinary knowledge and for producing a descriptive tool for application (Checkland, 1981).

2.3. Models and Simulation

A 'model' is generally defined as a simplified representation of a part of reality rather than a direct copy of reality (Loomis et al., 1979; France and Thornley, 1984), and 'modelling' is the process of developing that representation (Sowell and Ward, 1997). A mathematical model is one way of representing and studying a system and enables the study of responses in terms of logical and quantitative relationships (Yin and van Laar, 2005.). Models may include a range of mathematical equations and rules defining and describing a system (Barrett and Nearing, 1998) and are powerful tools to test hypotheses, synthesise knowledge, describe and understand complex systems such as processes that determine the system's behaviour, and to compare different scenarios (Marcelis et al., 1998; Hammer et al., 2002). Models should not be overloaded with unnecessary details and have minimum data requirements (Sinclair and Seligman, 1996). Models are, therefore, commonly kept as simple as possible to sufficiently describe a system or component of a system at a level of accuracy suited to the objectives of the task provided (de Wit and Goudriaan, 1978; Dent and Thornton, 1988). However, this simplification is arguably the greatest drawback for producing a comprehensible, operational representation of a part of reality (de Wit and Van Keulen, 1987; Hammer et al., 2002).

Models are commonly classified as either descriptive (empirical) or explanatory (mechanistic) based on their characteristics for understanding a system, although there are different schemas to classify models (Stapper, 1986). Descriptive models include statistical, regression, and empirical models. They are often labelled 'black-box models' as they reflect little or none of the mechanisms that are the cause of the behaviour of a system. Descriptive models are primarily based on functional relationships between observed input and observed output, which can offer a precise description of the observations on which they are based with predictions of known errors (Johnes et al., 2002). However, extrapolation of outputs from descriptive models for other conditions outside the range of input data upon which they are based is often difficult (Marcelis et al., 1998). In other words, caution is required when applying descriptive models to conditions beyond which the model was derived. On the other hand, explanatory models consist of quantitative descriptions of the various mechanisms and processes underlying the system of interest (Penning de Vries et al., 1989). The advantage of explanatory models is that parameters estimated at one level can predict results at the next higher level without calibrating or deriving a new parameter from independent experiments (Hoogenboom et al., 1994; Boote et al., 1996). As a consequence, the capability of explanatory models in extrapolating results for new circumstances is more acceptable than in the case of empirical models (Jame and Cutforth, 1996). However, in the case of complex mechanistic models, validation may be difficult to undertake for broader generalisations due to lack of well-defined statistical properties (Johnes et al., 2002).

Many of the crop models arise mainly from the knowledge or understanding of physiology, agro-climatic environments and biochemical processes rather than from empirical or statistical relationships (Boote et al., 2013; Craufurd et al., 2013) that make crop models capable of simulating both temporal and spatial dynamics of crop yields. As crop models are mainly mechanistic or process-based (Monteith, 1996; Sinclair et al., 2005), they are effective to understand the interaction effects of genotype, environment and management (G×E×M) (Jones et al., 2003; Keating et al., 2003; Messina et al., 2009) on crop growth, development, yield (Sinclair and Seligman, 2000). In other words, the crop model is able to simulate the various underlying physiological processes as they respond to environmental changes and affect grain yield and biomass formation (Asseng et al., 2013). Therefore, explanatory models, more so than descriptive models, allow for testing hypotheses and synthesising knowledge as well as facilitating comprehension of complex systems (Marcelis et al., 1998). Crop models usually contain sub-models at least one hierarchical level deeper than the response to be described (e.g., radiation-use efficiency is a process one hierarchical level below that which determines crop biomass accumulation). At the lowest hierarchical level, sub-models in an explanatory model are descriptive and the model's ability to explain the number of hierarchical limits output levels (Aumann, 2007). Regardless of whether a system is represented by a descriptive or explanatory model, both models are based on mathematical relationships between the different components within the system as well as the effects of environment on those components (Jones and Luyten, 1998).

Farming systems are primarily affected by the complex and dynamic interactions between weather, crop growth and development, soil, and management regimes. A simulation model is meant to simulate the interaction of the environmental heterogeneity and management alternatives. 'Simulation' is defined as the process of using a model, or models, to follow changes in a system over time (Wallach et al., 2014), most often requiring computing resources to run the simulations and often referred to us as computer models (Loewer et al., 1998). Simulation of agricultural process involve a complex set of equations for calculating a dynamic change of a state variable of the system for a specified set of input variable, which often use computer for computational purpose (Barrett and Nearing, 1998; Jones and Luyten, 1998). Computer models include the processes necessary for operationalising or solving a model to mimic real system behaviour. A computer simulation model consists of a structure (i.e., the equations that describe quantitatively how variables and processes are related) and parameters (i.e., numerical values in equations that determine their relative importance) (Kropff and Spitters, 1992). The model description includes all the equations of processes that cause change to its components, all the environmental variables affecting it, properties of system components and the underlying assumptions to develop a particular model (Asseng et al., 2013; Wallach et al., 2014).

The mathematical expressions used in simulation modelling may include both statistical and mechanistic approaches. According to France and Thornley (1984), simulation models can be classified based on time and the type of information generated. In particular, static models do not contain time as a variable, while dynamic models include time as a deriving variable to describe variation of a system or its components. On the other hand, deterministic models provide information on the mean response of a system to a change in one of its input variables (i.e., direct relationship between measurable and derived inputs without uncertainty) while stochastic models are described by probability concepts. The simulation process involves a number of steps including the development of computer logic and flow diagrams, writing of computer codes and implementation of the code to produce desired outputs (Jones and Lutyn, 1998).

2.4. Advancements in Crop Models

Crop simulation models combine mathematical equations and algorithms to represent logic that conceptually represents a simplified crop production system (Ritchie, 1991). Crop simulation models are mainly mechanistic or process-based as opposed to statistical or empirical models (Craufurd et al., 2013). Since the 1960s, many simulation models have been developed to describe the growth potential of a wide number of crops in relation to their physical environment (Matthews et al., 2002). For instance, simulation models have been used to express biomass growth as a function of the solar radiation interception (Wilson et al., 1995).

During the 1970s, modelling efforts were devoted to building theories and equations of various individual processes in agricultural systems (van Keulen et al., 1982; Penning de Vries et al., 1989) and the 1980s saw the development of whole agricultural system models (Hoogenboom et al., 1994; McCown et al., 1996; Reynolds and Acock, 1997; Hammer, 1998; Wang and Engel, 2000). Much of this work began at Wageningen University, Netherlands. Simulation models of increasing complexity continued to be developed in the 1990s and 2000s, e.g., DAISY (Hansen et al., 1991), ORYZA (Kropff et al., 1994), OZCOT (Hearn, 1994), DSSAT (Jones et al., 2003), CropSyst (Stöckle et al., 2003), APSIM (McCown et al., 1996; Holzworth et al., 2014), RZWQM (Ahuja et al., 2000), and Hybrid-maize (Yang et al., 2004).

Crop models vary in their structure, complexity and functionality but have four key components, including the major processes within the components that are responsible for regulating the dynamics of the system. These are: (i) plant development (the progression of a plant as it moves through different phenological phases); (ii) CO_2 capture (potential growth in terms of dry weight driven by temperature and solar radiation); (iii) water capture; and (iv) N and phosphorus capture (Probert, 2004; Delve et al., 2009; Donatelli and Confalonieri, 2011; Craufurd et al., 2013). The components are expressed in terms of both state/rate variables and process functions (also termed 'subroutines') (Wang et al., 2002).

The development of most crop-oriented design models has been fragmented resulting in a lack of scientific transparency and code efficiency, which has made it difficult to compare modelling approaches at the component level as well as enable automatic transfer of any improvements across crop models (Wang et al., 2002). Advances in crop modelling have been achieved by integrating knowledge from different disciplines (Jones et al., 2001). For example, advanced software engineering techniques have led to modular frameworks, consisting of libraries of modules from which selection can be easily made (Hammer, 1998; Jones et al., 2001; Wang et al., 2002; Adam et al., 2011). Modular frameworks have greatly facilitated the exchange of model components (e.g., modules and routines) in crop modelling

(Reynolds and Acock, 1997; Jones et al., 2001; Wang et al., 2002; Adam et al., 2011). Widely recognised modular crop modelling platforms are OMS (David et al., 2002), TIME (Rahman et al., 2003), APSIM (McCown et al., 1996), DSSAT (Jones et al., 2003) or APES (Donatelli et al., 2010), and CROSPAL (Adam et al., 2010).

Models are an important research tool as they provide a low-cost way to explore agricultural system performance along with environmental interactions over long time scales. Crop simulation models have been widely applied to understand the impacts of climate variability on crop production systems as well as to evaluate alternative management options for managing climate risk and uncertainty (Challinor et al., 2009; Meza and Silva, 2009; Kassie et al., 2014). Field research provides one approach of understanding treatment effects on crop yields; however, extrapolation of these results to other conditions may be limited. In contrast, crop models are capable of simulating many scenarios to explore both the temporal and spatial dynamics of crop yields (Hansen, 2005) because they explicitly consider the main plant physiological and biochemical processes as well as heterogeneous agro-climatic conditions (Jame and Cutforth, 1996). For example, Dixit et al. (2011) highlighted the challenge of capturing crop responses to rainfall variability using agronomic field research. In particular, the field research typically runs for short time (e.g., 3–5 years), and may be insufficient to examine the long-term impact of the management options under investigation. In terms of climate risk management, crop modelling has proven effective for assessing climate-induced risk for a wide range of soil and crop management options (Hansen and Jones, 2000; Keating and McCown, 2001; Meinke et al., 2001; Keating et al., 2003; Hansen, 2005; Cooper et al., 2008; Moeller et al., 2008).

2.5. Crop modelling as Part of Participatory Research: Case Studies

Since the 1960s, crop modelling approaches have played an important role in examining the impact of management options under a range of environmental conditions, as defined by the combination of weather and soil-type at a specific location's 'representative farm'. The outputs from this theoretical research have been used to develop recommendations for crop production (McCown, 2001). However, the majority of these 'best bet' practices have failed to address long-term problems in real-world situations (Keating and McCown, 2001; McCown and Parton, 2006; Woodward et al., 2008; Le Gal et al., 2011). Such modelling approaches have been criticised for failing to address the objectives, preferences and expectations of farmers (Carberry et al., 2004; Woodward et al., 2008; McCown et al., 2009; Martin et al., 2011).

An extensive review of system modelling research of the past 30 years showed that the majority of the simulation modelling practices had been developed without the direct participation of farmers (Woodward et al. 2008). Farmer participation could be increased by directly consulting them in simulation scenarios, allowing the system modelling approach to be used as a tool for facilitating experiential learning rather than for designing 'best practices' (McCown, 2001). However, there is recent evidence that clearly shows how simulation-aided discussions about crop management have facilitated management intervention (Keating and McCown, 2001). This calls for the relevance of participatory approaches using simulations to drive relevant and significant intervention (Robertson et al., 2000; Keating and McCown, 2001; Meinke et al., 2001).

Participatory modelling is a general term used to describe a number of specific methodologies and processes associated with the integration of system modelling and participation from stakeholders (Gaddis and Voinov, 2008). These methods and processes involve stakeholder involvement at different stages of the overall modelling exercise spanning from involving stakeholders (not necessarily model users) in the construction and use of models as well as their involvement only in the use of models (Dreyer and Renn, 2011). There is value in client participation in problem definition, model design, testing, and evaluation phases of model-based research projects (Woodward et al., 2008). The theory is that simulation modelling enables participants to learn by 'virtual' experience with the unique advantages that any mistakes and losses are not actual (McCown et al., 2009). Models may be effective tools to facilitate dialogue, share learning, and potentially enhance uptake of new practices such as improving food security, within participatory research approaches (Meinke et al., 2001; McCown et al., 2002; Carberry et al., 2004; Ncube et al., 2007; Carberry et al., 2009; Rodriguez et al., 2014). For effective application, Carberry et al. (2002) and McCown et al. (2009) asserted that a model should be flexible and comprehensive in its capability to address relevant issues in farm management decision-making. As a result, a simulation model can be used to jointly create a 'virtual world' wherein simulation experiments may be conducted to facilitate learning. The innovation is that this process may change the way an actual system is managed. Connectivity among key players, i.e., researchers, farmers and extension persons, through simulation-aided discussions about crop management is essential to facilitate dialogue about management options that are relevant and significant to decision makers (Keating and McCown, 2001; McCown, 2001; Hammer et al., 2002). Virtual experiments and discussions of 'what if?' analyses could be a good example of computer-supported thought experiments in which the information can be used for strategic learning and for supporting farmers in situation planning and decision-making (McCown et al., 2012). For instance, simulation-aided discussions that engage farmers and their advisors are essential to facilitate the dialogue about management options and significant to changes to management practices (Keating and McCown, 2001; McCown, 2001; Hammer et al., 2002; Hochman et al., 2009, 2017b).

For a simulation model to be taken seriously by farmers and potentially influence management decisions, the model must be seen as credible (Carberry et al., 2002). Models are judged as being credible or 'good' if simulation outputs correspond adequately to empirical measurements. As criteria of model evaluation, Carberry et al. (2009) suggested that the needs of farmers and consultants for model assessment should be included for a model to be useful in practice. Rodriguez et al. (2014) demonstrated farmers' evaluation as a practical, albeit unconventional, form of model validation. They evaluated a simulation model by asking participating farmers whether they agreed with model outputs in showing the expected crop yields, gross margins, business profits and their variability. Thus, farmers judged the model's 'goodness' based on their practical experience. Such model evaluations by farmers are important to create mutual understanding and credibility among farmers and scientists (Carberry et al., 2009). Carberry et al. (2009) noticed that farmers who developed trust in, and gained appreciation of, the model's abilities were motivated to participate in a participatory modelling project. As a result of the research process, farmers were able to learn which factors make a difference in their planning and decision-making. On the other side, computer-aided discussions with farmers and advisors influences the way researchers understand farmers' reality and subsequently identify knowledge gaps (Le Gal et al., 2011).

Involvement of farmers may take place at different stages of the process from model design to scenario evaluation (e.g., Castelan-Ortega et al., 2003; Lisson et al., 2010). For example, in PAR (Meinke et al., 2001; McCown, 2001; Ncube et al., 2007), farmers actively engage in discussions about building realistic scenarios for the computer simulations, which will then be run for the farmers to get their reactions and suggestions for possible improvements of the simulation scenarios (Meinke et al., 2001; McCown, 2001; Ncube et al., 2007).

Over the past 30 years, computer-based modelling has made major advancements, but its ability to influence management decisions remains limited (Woodward et al., 2008; McCown et al., 2009). One participatory modelling approach combines crop modelling with PAR: The Farmers', Advisers', Researchers', Monitoring, Simulation, Communication And Performance Evaluation approach (FARMSCAPE) is an example of one successful participatory modelling approach that has influenced management practices of farmers using science-based research (McCown and Parton, 2006). Developed in Australia, FARMSCAPE has been used nationally to successfully manage large commercial farms (Carberry et al., 2002; McCown and Parton, 2006; McCown et al., 2009). Farmers have come to value the FARMSCAPE approach because of its contribution in addressing specific questions regarding management in benchmarking, tactical planning, yield forecasting, and scenario exploration (Hochman et al., 2000; Carberry et al., 2002). The process involves a series of facilitated discussions with farmers about specific questions using 'what if' scenarios. Farmers were able to appreciate the outputs produced by the simulations, which were credible and meaningful, while the researchers were surprised that the simulation was relevant to farmers and could be further applied within an action research framework (Carberry et al., 2004). Following the Australian experience of using FARMSCAPE, this approach has also been adapted for small-scale farmers in Indonesia, South Africa and Zimbabwe (Carberry et al., 2004). This approach has successfully been used to increase the adoption of best-bet technologies, (e.g., novel forages and animal feeding practices) in Indonesia (Lisson et al., 2010). Another preliminary study in South Africa and Zimbabwe has also shown the potential of adapting FARMSCAPE to facilitate discussions with farmers and subsequently help in identifying alternative management options being tested using on-farm experiments (Carberry et al., 2004).

An evaluation of the long-term use of computer-based models found that benchmarking contributed to the sustained adoption of technologies by farmers (Lisson et al., 2010) and was a key activity in a 'thought experiment' for diagnosing what had, and had not, been achieved, and the possible opportunities for enhancing yield that may be attainable (McCown et al., 2012). In rain-fed cropping systems, the gap between attainable and actual yield can be confounded by bio-physical variation such as availability of water between sites and seasons (Sadras and Angus, 2006). In this case, evaluation of water use by comparing the attainable and the actual yield provided a sound basis for yield benchmarking (Sadras and Angus, 2006; Carberry et al., 2009). Realistic simulations of crop yields over many seasons and situations created a strong validation case for crop models such as APSIM (Carberry et al., 2009). Furthermore, benchmarking is good for enhancing learning by both formulating expectations and understanding of casual processes (Hochman, 2000; McCown et al., 2001). Benchmarking is an important first step in farming systems design developed in close consultation between farmers and researchers through the PAR (Lisson et al., 2010). Benchmarking has also been used for subsequent design and model-based evaluation of alternative management scenarios (Martin et al., 2011) and provides thought-provoking feedback to farmers, i.e., feedback indicating the existence of a problem or the possibilities for improvement.

In a research project carried out by McCown (2012), it was shown that scenario analysis could support thought experiments in shaping expectations by providing a historical perspective of the scenario results – history of the future – as well as bringing profound changes in strategic learning and system design. It could also assist tactical decision-making where agronomic management options for the current season are evaluated based on the known status of the system early in the season. In this case, the dialogue around the simulation analyses is more important than the underpinning models, although it is clearly reliant on their existence and reliability (Keating and McCown, 2001; McCown, 2001).

In summary, the participatory approach can facilitate the design and implementation of innovations by taking into account the needs, constraints, and knowledge of farmers and this could assist with evaluating the feasibility of a proposed innovation (Vayssières et al., 2009). Furthermore, interventions developed from models, in consultation with farmers, have led to tangible changes in management practices (Carberry et al., 2002; McCown and Parton, 2006; Lisson et al., 2010). Application of modelling tools within the framework of participatory research has proven to be effective in: (i) gaining insights into the functioning of complex farming systems; (ii) generating awareness of the potential impacts of different management options; (iii) identifying opportunities for incremental or transformational changes in farming systems; (iv) assessing the climatic risk of alternative technologies; (v) analysis of economic trade-offs of alternative resource allocation; and (vi) contributing to learning about farm management practices via computer-aided discussions with farmers (Carberry et al., 2004; Ncube et al., 2007; Carberry et al., 2009; Lisson et al., 2010).

2.6. Participatory Modelling for minimising Climate Risk

The term ‘risk’ is a very broad term that is very difficult to define and measure (Just et al., 2003; Hardaker et al., 2004a) and has various definitions depending on the subject matter (Cross, 2000). Although there is no universally accepted definition of risk, in this thesis risk is defined as “uncertainty with the consequences” (Hardaker et al., 2004a) in which the decision maker assesses in advance the probability distributions of the possible consequences or outcomes (Cross, 2000). The term ‘uncertainty’ is defined as lack of perfect knowledge of the future (Hardaker et al., 2004a) meaning that the decision maker does not know the probabilities of the possible outcomes or consequences. In terms of farming systems, production risk arises from uncertainty related to crop or livestock performance due to climate variability (Hardaker et al., 2004a). Incomplete or imperfect information on past and present conditions is one of the main constraints for decision-making, which entails a degree of uncertainty about the consequences. Such decisions are then, by definition, classed as risky (Bacic et al., 2006). When making decisions, farmers largely follow a practical approach based on their intuitive thinking in response to perceived changes in the operational environment (Schwartz and Sharpe, 2006). This is a heuristic manner of decision-making as simple ‘rules of thumb’ are applied to make quicker decisions bypassing rational processes (Long and Cooper, 2011). This may often lead to actions that are often biased and result in outcomes that are not robust, particularly under climate variability (Nicholls et al., 1999). Hogarth (2001) suggested that farmers’ learning capability in dryland environments may be inhibited by a ‘‘wicked’’ learning structure. This largely occurs because of the random nature of seasonal climate events as well as ignoring information about current causal states in the ‘production system’ and its potential to help predict future outcome states (McCown et al., 2009).

Crop system modelling may offer a more robust and rational approach for decision-making than the heuristic approach because it can provide a ‘virtual experience’ about the uncertainty related to the probabilities of possible outcomes in the long-run – it creates a climate-determined stochastic sequence that approximates what farmers’ face over time (McCown et al., 2012). Learning about the effects of climate variability on crop yield using simulation modelling can replace their intuitive understanding with expectations of likelihoods derived from quantitative analyses (McCown et al., 2012) and therefore help to quantify the risks and uncertainties of different management options under climate variability (Meinke et al., 2001;

McCown et al., 2009). In this way, crop simulation modelling can assist farmers make informed decisions as they can directly learn the impact of their decision-making under climate variability (Long and Cooper, 2011). In analyses quantifying risks, farmers are interested in trade-offs between expected net returns and the overall variability in net return, not just the average (Woodward et al., 2008). McCown et al. (2001) pointed out that farmers need to be able to explore the consequences of diverse actions for different soil conditions to make sense of the yield variability brought about by variable climate. When making decisions in climatically variable environments, it is unlikely there will be a single strategy or practice that will be appropriate across all years. There is a trade-off between the economic return of a strategy and its riskiness (Anderson et al., 1977; Hardaker et. al., 2004a and b).

Systems approaches are useful to understand how climate interacts with the farming system (Hayman et al., 2011). In dryland systems, where climate is a major source of risk, system analysis is valuable in identifying trade-offs. For example, strategies that are tailored to minimise losses in bad years forgo profit when the seasons are good (Hayman et al., 2011). Whatever decisions farmers make, many of the decisions are to improve the economic position of the farm business (Hardaker and Lien, 2010; Long and Cooper, 2011). However, most crop models quantify the effects of climate variability on production with rare analyses to quantify the effect of economic welfare (Van Wijk et al., 2014). While economic returns are of primary importance, a number of decisions that farmers must make are also based on perceived risks of potential economic loss due to climate variability along with other factors (Meinke et al., 2001). Realising the heterogeneity between farms and thus the importance of the farmer’s perceptions and goals, economists are accepting farmers’ behaviour should not be understood only through maximisation of profit (Colin and Crawford, 2000). So, the value of some crop system models can be improved by combining with economic analytical tools (Hansen, 2005).

There are two useful tools used in economic analysis which assist in comparing strategies, which differ in their trade-offs between returns and risk. One of the major economic analytical tools used to evaluate different management strategies is the efficiency frontier in mean-variance (E-V) space (Muchow et al., 1991; Keating et al., 1992, 1993). This tool compares the trade-offs between the possible returns and risks of alternative strategies (Anderson et al., 1977; Hardaker et al., 2004a). An efficiency frontier in E-V space assesses different strategies by delineating the plot of mean against standard deviation. In this approach, the standard deviation (statistical variance) is used as a surrogate for risk (Anderson et al., 1977; Hardaker et al., 2004a). An alternative economic analytical tool is stochastic dominance analysis, which is used to compare the cumulative distribution functions (CDF) of various strategies and to provide a partial ordering of risky alternatives based on specified utility functions of risk-averse farmers (Anderson et al., 1974; Hardaker et al., 2004b).

The more farmers experience and discuss a particular subject, the better their intuition will be. If farmers are to make decisions using a logical, rational process there is often a need to simplify assumptions and to limit the available information and thoroughness of the analysis (Long and Cooper, 2011). In contrast, the information provided by simulation outputs and the associated economic analyses can be complex and may not be easily accessible by decision-makers (Just et al., 2003). To improve the knowledge transfer of such complex information, Murray et al. (2005) suggested that farmers be advised with different interactive styles and group-specific information. Improved methods in extension (e.g., hand-drawn graphs or simple histograms plotted against year of simulation or frequency-based probabilities) will ensure farmers are able to easily access the risk information and make informed decisions (Dimes et al., 2003; Carberry et. al., 2004; Ncube et al., 2007).

2.7. Conclusion

In drylands, smallholder farmers are operating under complex and fragile environments, where high spatial and temporal variability in seasonal climate is arguably the main source of risk and uncertainty for crop production. This makes the challenge of achieving food security more difficult. To improve productivity and resilience of the smallholder farming systems in the face of climate risk and uncertainty, all interventions from research and extension advisory services should be tailored to develop location-specific agronomic and technological recommendations that are effective within farmers' values (production objectives and aspirations), resource endowment and capacity to accept risk. Conventional agronomic experiments, which are usually conducted over relatively short periods at limited sites, might be useful to get some insights on cropping system performance in response to change in agronomic and technological interventions. In farming systems having highly variable climate and soil, however, it is physically difficult and extremely costly to apply this approach for obtaining sufficient and valuable information. Just as the bio-physical settings of the farming systems are complex and variable, so are the socio-economic aspects of the farm households.

Advances in describing bio-physical processes in agricultural production systems have provided better capabilities for understanding and modelling of the key system processes related to crop growth and development, water and N dynamics. Furthermore, it enables quantification of crop attributes and the limiting resources (e.g., soil N and water) as a consequence of the various changes in agronomic practices. Crop models are becoming more comprehensive in exploring production-risk trade-offs associated with the various management options under investigation. For example, the value of crop modelling has been greatly improved through interactions with decision makers via discussions of decision options and risks so that it can better support and guide farmers' agronomic responses and decisions on allocation of their limited resources under variable and uncertain climatic conditions. Put simply, long-term simulation scenarios can be analysed to provide quantified information on climate-induced yield variability due to change in agronomic management in situations of risk associated with climate uncertainties. However, technical solutions for key problems of the farming systems are unlikely to bring any practical change unless the vast majority of smallholder farmers adopt the technological interventions that are recommended by research and extension services. Using a participatory research approach and actively engaging farmers through dialogue, rather than considering farmers as passive recipients of technology could easily encourage farmers to make changes in their management practices.

For targeting effective recommendations that are suitable to the bio-physical environment and desirable to the socio-economic conditions of the farming community, there is no task as important as gaining good insight into the various aspects of the farming systems at the targeted locations under investigation. Given the fact that farming systems are highly diverse and variable in nature, it is unrealistic to presume that single technical solutions will fit the various situations of the farming systems. To address some of these issues, systems research can be used as a feasible approach to effectively and efficiently study the complex farming systems while accounting for the various farmers' perspectives and their socio-economic aspects. Combining a participatory research approach and crop modelling and simulation capability within the innovation process can be used to jointly gain a 'virtual experience' wherein experiments may be conducted to facilitate co-learning among decision makers and extension advisors regarding performance of the relevant system attributes as a consequence of new technologies, practices or management decision options. In broad terms, model-aided simulation has had little relevance in farmers' decision-making. There is, however, some evidence where model-aided simulation can be successfully applied to facilitate co-learning among key actors (e.g., farmers, researchers, or extension persons). FARMSCAPE is a typical example of an interface that takes a systems approach one step further by coupling simulation of relevant farming events and actions into the context of farmers learning and problem solving capacity within a participatory research approach. Some evidence from the FARMSCAPE success story suggest that participatory modelling is effective as a systems approach to enhance technology uptake by formulating the most feasible agronomic or technical solutions that are in tune with the climatic conditions while adaptable to specific socio-economic conditions.

Participatory modelling approaches enable decision-makers to interact via discussions of the various agronomic management options and their production risk. Discussion outcomes can assist in generating awareness on the potential impacts of the various intervention strategies that ultimately assist in developing effective decision support suiting risk-averse and resource-constrained farmers under climate risk and uncertainty. As the financial consequences of various management strategies are often relevant to farmers' decisions at the farm scale, integrated crop models interfaced with economic or agent based models can provide information on detailed interactions and trade-offs between competing objectives on this level. For example, information on quantified profit-risk trade-offs associated with management options can be available for discussion with farmers. Farmers can, therefore, visualise all available alternatives on what they can achieve and what approach better suits the unique conditions of their particular farm and their personal circumstances. Model outputs for the simulation scenarios of varying risk profile can be effectively aligned with farmers' risk preference and resource status, and within their capacity of translating the available information. Ultimately, effective decision support can be developed according to cultural-behavioural and economic characteristics of the farmers that can, as a result, enhance the productivity and resilience of their farming system in the face of present and future climate uncertainties.

A systems approach provides researchers and decision makers with the most efficient means to better use our understanding of the bio-physical condition and farmer's choices and socio-economic reality in their local contexts. However, for systems approaches to be successfully applied, there is a need to have strong integration among the various key actors. Advisors from agricultural research, development and extension groups need to make a deliberate effort to dedicate themselves in developing effective interventions for sustainable intensification of production in smallholder farms under increased climate variability and anticipated climate change.

Chapter 3 Farmers' perceptions, knowledge of, and responses to climate variability in the Central Rift Valley of Ethiopia

Abstract

The vast majority of smallholder farmers in the semi-arid region of Central Rift Valley (CRV) Ethiopia, where there is a high variability in seasonal rainfall pattern, depend on rain-fed agriculture for their livelihood. Rapid Rural Appraisals (RRAs) were conducted at Bosset and Adamitulu Jido-Kombolcha (AJK) districts in the CRV for establishing a better understanding of farmers' perceptions of, and response to climate variability. During the RRAs, key-informant interviews and focus group discussions (FGDs) were employed to collect relevant information from participating farmers at the targeted districts. In these districts maize (*Zea mays* L.) is dominantly grown as a major staple crop for ensuring food security at the house level. At the targeted villages in the study districts, farmers' subjective assessments of the perceived climate variability and risks were also evaluated in comparison with historical climatic records that were collected from the closest meteorological stations located within 15–20 km of both study villages. The study also examined how farmers translate their understanding of existing climate variability into management decisions as guided by their local knowledge and past experience (heuristics). According to farmers' responses, they were aware of their local climate, particularly the inter- and intra-seasonal rainfall variability. In the FGDs, the farmers in both districts were also able to recollect historical climate patterns as far back as 20 years. When the perceived and measured variability in rainfall pattern was compared, farmers rated the historical seasonal climate reasonably well as their responses mainly concurred with the historical climate records. Based on their recall and experience of the past, farmers classified the seasonal climate as 'good', 'average', or 'bad' based on the seasonal rainfall pattern in relation to crop production. Farmers considered the date of the rainy season onset of primary importance followed by the occurrence of dry spells at flowering and grain-filling stages of maize, and the consequence thereof on maize productivity. The study found that farmers have nearly consistent perceptions of, and criteria, to describe various seasonal climatic conditions. Farmers responded to the variable climate by manipulating their agronomic responses according to the actual and expected seasonal rainfall pattern. Although all farmers did not respond in the same manner, many of the key decisions were made at sowing, including what

crop or cultivar to sow and the portion of land being allocated to the different major crops. If there is early onset of rain between March and May (*Belg* season), many farmers would like to allocate a significant portion of their land to maize because it is a priority crop to meet their dietary needs and to harvest enough stover that can be used as a source of dry season feed for their cattle. If rain begins in the *Belg* season, around 60% of the farmers at AJK said they would prefer to sow their late-maturing cultivar. On the contrary, nearly 70% of the farmers at Bosset explained that they were losing confidence in the reliability of rain in the *Belg* season due to a high risk of post-sowing dry spells that can often cause significant yield reduction or total crop failure. As a result, the majority of farmers at Bosset district opted to wait for the main *Kiremt* season rain. Farmers explained they use different maize cultivars of varying maturity that are suited for the variable onset of seasonal rain. Around 72% of the respondents in the study area stated that they are not willing to apply commercial fertiliser because of lack of capital, its high cost and/or considerable variability in economic return, and it often involved the risk of insufficient compensation to cover the cost of investment in fertiliser. However, around 19% of the farmers explained that they did not expect any advantage of yield gain from applying commercial fertiliser to their maize crop. On the whole, farmers identified sowing time, cultivar choice, and fertiliser application as the most important agronomic decisions to make in effectively managing the challenge of climate variability and risk. Although many farmers do their key agronomic decisions when sowing opportunities occur, they always confront risk as a consequence of decisions made at sowing. The effect of climatic risks and their interaction with crop management decisions could be considerably enhanced via model-assisted discussions in providing an opportunity for co-learning and ultimately understanding potential outcomes when agronomic practices are changed. The ultimate goal would be to explore management opportunities that can reduce the risk of low yields and crop failure thereby improving the long-term productivity or economic return of smallholder farms in conditions of risks associated with seasonal climate uncertainties.

3.1. Introduction

In the semi-arid region of Central Rift Valley (CRV) Ethiopia, smallholder farmers tend to follow traditional strategies to manage the challenge of climate variability and its associated risk based on their understanding of the local climate and past experience (Fujisaka et al., 1996a and b). Anecdotal evidence has showed that smallholder farmers view the recommendations from research and extension services as "weather insensitive" (Dimes, 2011; Dixit et al., 2011). The recommended technologies should include adequate information on the risks and returns of the proposed technologies that can support farmers to make informed decisions in the face of climatic risk and uncertainty (Keating et al., 1991; Rao et al., 2011). Likewise, extension providers need to understand how to tailor their advice to prevailing climatic conditions based on the best available research outcomes (Dixit et al., 2011). In addition to that, many of the recommendations have to be sensitive to the farmers' socio-economic environment when developing interventions for possible adoption (Snapp et al., 2003; Tittonell et al., 2010). By doing this, research and extension services can shape the effort on agricultural research, development and extension (RD&E) towards developing effective recommendations that are in tune with the variable climate and adaptable to specific conditions of the smallholder farmers who are characterised by poor resource endowment and technical skill, as well as risk aversion behaviour (Slegers, 2008).

Therefore, agronomic recommendations need to be flexible and must meet the production and socio-economic objectives of the targeted smallholder farming communities in the dryland regions (Fujisaka et al., 1996a; Gadgil et al., 2002; Quinn et al., 2003; Cooper et al., 2008; Rao et al., 2011). This suggests that understanding farmers' perceptions of, and management responses to climate variability is the critical prerequisite for developing promising technological interventions that can ultimately influence on-farm decision-making (Fujisaka et al., 1996a and b; Rao et al., 2011; Stern et al., 2011). A close investigation of the existing local practices and decision making process of smallholder farmers is therefore an essential first step in developing demand-driven and well-targeted agronomic and technological interventions that can fit into the context of farmers' local practices and their specific socio-economic reality. This study aimed at providing insights into how farmers of the CRV perceive climate variability, particularly rainfall variability, and how their understanding of climate variability translates into farm management decisions and actions. Awareness, use, and value of indigenous and evidence based seasonal climate forecasts in tailoring their cropping decisions was also examined. Better knowledge and deeper insights into the above-mentioned subjects was gained through farm surveys, informal discussions, in-depth interviews and group discussions in which farmers were actively engaged to express their perceptions, views and understanding.

3.2. Methods

3.2.1. Description of the study area

The study was conducted in six villages in the districts of Bosset and Adamitulu Jido-Kombolcha (AJK), East Shewa zone, Oromia Regional State, Ethiopia (Fig. 3.1). In the study districts of Bosset and AJK, over 70% and 80% of the population live in rural areas (CSA, 2008). The majority of the rural population is directly or indirectly employed in agriculture and related sectors (Kassie et al., 2013b; Getnet et al., 2014).

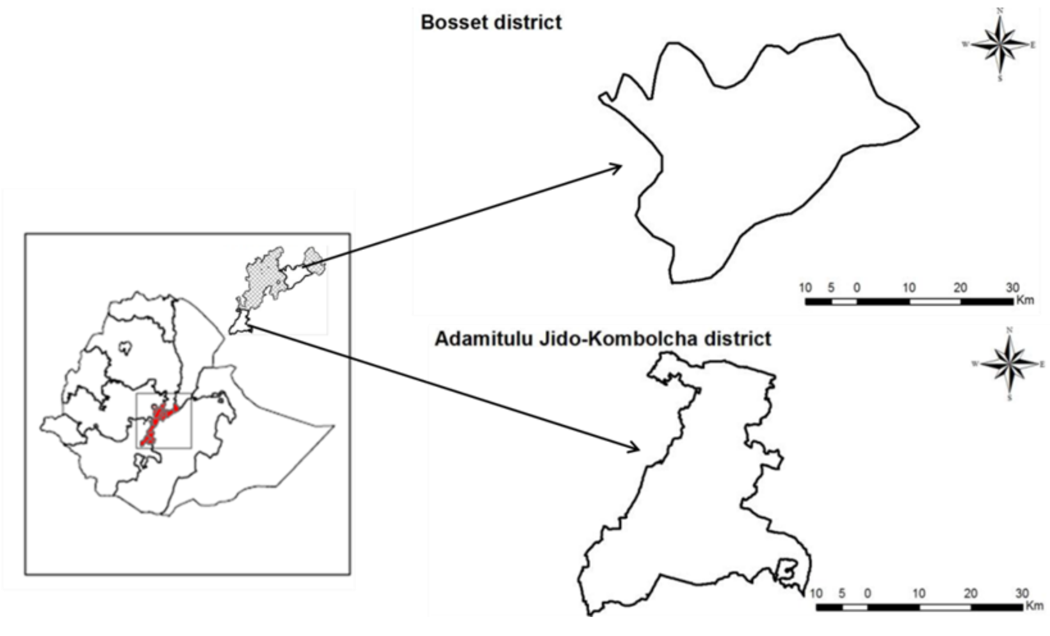


Figure 3.1: Study districts in the Oromia region of the Central Rift Valley, Ethiopia.

3.2.2. Situation analysis

Environment

The landscapes of the CRV are characterised by strong topographic contrasts. The rift formation continues, and is associated with extensive volcanism (Ebinger et al., 1993). The valley floor of the CRV is 1500-1700 m.a.s.l., and bound by western and eastern escarpments with altitudes of over 4000 m (Jansen et al., 2007). The climate of the CRV region is tropical and semi-arid (Hengsdijk and Jansen, 2006; Meshesha et al., 2012). Rainfall in the region is generally bi-modal (Kassie et al., 2014). The short rainy season (March-May), locally known as *Belg*, is characterised by light and highly variable rainfall (Table 3.1). The *Belg* rainfall is primarily influenced by humid easterly and south-easterly winds from the Indian Ocean (Seleshi and Zanke, 2004). The main rainy season (June–September) is locally called *Kiremt*, and provides more reliable, less variable rainfall for crop production (Table 3.1). The *Kiremt* rainfall contributes 70–90% of the annual rainfall (Conway, 2000; Seleshi and Zanke, 2004; Hengsdijk and Jansen, 2006; NMA, 2007). *Kiremt* rainfall originates from both the Atlantic and Indian oceans, and is largely influenced by northward migration of the Inter Tropical Convergence Zone (ITCZ). The length of the *Kirmet* season varies regionally depending on the duration of the predominant winds (NMSA, 2001).

Table 3.1: Rainfall statistics from two meteorological stations in the study region.

	Melkassa [a]			Adamitulu[b]		
	Average (mm)	Median (mm)	CV% [c]	Average (mm)	Median (mm)	CV%
Annual rainfall	825	814	19	811	741	29
Belg rainfall	165	134	45	229	223	48
Kiremt rainfall	555	544	21	469	446	30

[a] Represents villages in the Bosset district

[b]Represents villages in the Adamitulu Jido-Kombolcha (AJK) district

[c]The coefficient of variation (CV%) was calculated as the ratio of the standard deviation and the mean multiplied by 100

The geological features of the CRV region are the result of Cenozoic volcano-tectonic and sedimentation processes. Thus, the parent soil material is largely derived from recent volcanic rocks; basalt, ignimbrites, lava, gneiss, volcanic ash, alluvium and pumice (Lemenih and Itanna, 2004; Zewdie, 2004; Itanna, 2005). The dominant soils in the districts of Bosset and AJK are classified as Haplic Andosols and Haplic Solonetz, respectively (Zewdie, 2004; Itanna, 2005). Both soil types have low levels of Nitrogen (N), phosphorus (P), soil organic matter, and in some cases poor physical structure (Itanna, 2005; Garedew et al., 2009; Mesfin et al., 2010).

3.2.3. Farming systems

The farming systems of the CRV are dominated by rain-fed cropping and mixed crop-livestock systems which generally sustain livelihoods at a subsistence level (Jansen et al., 2007; Kassie et al., 2013b; Getnet et al., 2014). Crop production is mainly cereal-based and maize (*Zea mays* L.) is the dominant crop. The other major crops grown are tef (*Eragrostis tef* [Zucc.] Trotter), wheat (*Triticum aestivum* L.), barley (*Hordeum vulgare* L.) and common bean (*Phaseolus vulgaris* L.). Crop production also supplies crop residues, which are grazed *in-situ* or collected and stored as feed for the livestock (Zeleke et al., 2004; Biazin et al., 2011). Cattle (*Bos primigenius*), goats (*Capra hircus*), and sheep (*Ovis aries*) are fed primarily by free grazing throughout the year (Yimer and Abdelkadir, 2010; Kassie et al., 2013a).

Traditionally, tillage involves repeated cultivation (3–5 times depending on the required soil tilth) with the local *maresha* plough (oxen-drawn implement with a single tine) combined with complete removal of residue (Rockström et al., 2009; Temesgen et al., 2009; Mesfin et al., 2010). In maize-based cropping, *shilshalo* is a traditional form of soil ridging conducted at about the 5- to 6-leaf stage of maize (approximately 35–40 days after sowing) to control weeds, to adjust plant density, conserve soil moisture, and accumulate fertile top-soil around plants to improve growth (Birhane et al., 2006; Biazin et al., 2012). Where sandy loam soils are prone to crusting, *shilshalo* is a means of breaking the surface crusts thereby enhancing soil water infiltration (Biazin et al., 2011; Biazin and Stroosnijder, 2012). In-crop weeds are typically controlled by hand-weeding. The frequency of hand-weeding depends on the availability of labour.

Land degradation caused by overgrazing, deforestation, and cultivation on steep slopes is an important factor for significant water erosion and soil fertility deterioration of cultivated lands (Jansen et al., 2007; Meshesha et al., 2012; Adimassu et al., 2012, 2013). Crop productivity is significantly constrained by low soil fertility (Senay and Verdin, 2003) since most of the local households do not apply fertiliser, or apply insufficient rates of commercial fertiliser or cattle manure to restore fertility and prevent the continuous depletion of mineral nutrients from their cultivated land (Biazin and Stroosnijder, 2012). Both N and P fertiliser in the form of urea-N and di-ammonium phosphate (DAP) may be applied at sowing, and N fertiliser may be top-dressed later at 4–5 weeks after sowing when *shilshalo* is practiced (Birhane et al., 2006). Top-dressing of N is conditional upon how well the maize crop is established, and the yield expectation. As a fertility maintenance strategy, many farmers also apply organic fertilisers (dominantly manure, and compost in a few cases) to their maize crop (Getnet et al., 2016). Many farmers usually construct animal enclosures (kraal) near the homestead as *in-situ* fertilisation of the previously cropped maize (ICRA, 1999).

Farmers manage seasonal rainfall variability by adjusting the maturity type of cultivars based on the commencement of the season. Farmers prefer to sow late-maturing maize cultivars (130–145-day) if rainfalls start in March to May. If rain starts in early- to mid-June, they opt to sow medium-maturing cultivars (110–130-day). They sow early-maturing maize cultivars (<110-day), if rains are very late (end of June) or if an early-sown crop failed. Farmers consider the end of June as the cut-off date for sowing maize, and no maize is sown thereafter (ICRA, 1999).

In using these traditional methods, farmers attempt to address production issues related to rainfall variability and low soil fertility. These are strategies devised by farmers based on their long-term experiences and perceptions of anticipated rainfall variability.

3.2.4. Rapid rural appraisals

Rapid rural appraisals (RRAs) were conducted in August–October 2012, with the assistance of local extension officers at the respective districts, to establish a better understanding of farmers' perceptions of, and response to climate variability. The RRAs include various activities, methods, and techniques for fast and effective collection of important information about a particular aspect of the farming system (e.g., Beebe, 1995; Townsley, 1996). In this study, the RRAs involved the (i) design of questionnaires for individual and focus-group interviewing, (ii) selection and recruitment of participating farmers in the study villages, (iii) FGDs, (iv) key-informant interviews (KIs), and (v) collection of secondary data on the socio-economic and bio-physical characteristics of the study districts. These different methods of inquiry and information gathering helped to generate more reliable data by minimising the chance of bias (Flick, 2002; Grix, 2010). Knowledge and insights therefore gained through all the above-mentioned methods.

For carrying out RRAs, the local extension officers were approached, in particular, to assist in selecting the targeted villages and participating farmers in the study districts. They also assisted in facilitating discussions in FGDs by acting as moderators to encourage and ensure the active participation of all members of the farmer groups to express their view. In Ethiopia, agriculture extension personnel at the district level work closely with farmers and would have detailed information on the respective study sites. For the study, local extension officers, who were working for the local bureau of agriculture at the targeted districts, were contacted to obtain more detailed information on the local farming systems, and for selecting the potential villages within each targeted district. Recruitment of farmers at the site was also done through the assistance of extension officers who approached potential farmers who were willing to participate in FGDs and interviews.

Both the focus groups questions and the interview questionnaire were designed in English but the interviews were conducted in Amharic and the responses were then back-translated into English. The translated English transcripts of the interviews were used for analysis. The major themes in the FGDs and the interview questionnaire are summarised in Table 3.2.

Table 3.2: Summary of information gathered in the focus groups discussions and the interview questionnaire.

Major theme	Questions related to:
Respondent information, farm characteristics and farming experience.	Location, gender, education, size of farm, and years of farming experience.
Perceptions, attitudes and knowledge of climate variability and climate risk.	How farmers describe seasonal climate variability: amount of rainfall, start of rainfall, duration, dry spells, and temperature. Farmers’ perceptions of climate risk in maize production. Criteria that farmers use to describe a good, an average, and a poor season for growing maize.
Key management decisions in light of climate variability.	Decisions farmers make to deal with climate variability.
Farmers’ awareness and use of seasonal climate information.	The type of weather or climate forecasts farmers use. Farmers’ understanding of scientific seasonal forecasting.

Sampling strategy and recruitment of participants

Two-sampling stage techniques were implemented. Firstly, 11 villages were chosen from the two study districts based on several factors, including maize grown as the major crop, occurrence of the major soil types of the region, and proximity to meteorological stations. Of these villages, three were selected from each of the two districts based on an initial survey conducted in consultation with local extension officers possessing expert knowledge on the respective study sites. Secondly, 50 farmers from each village (totalling 300 farmers), who each had at least 10 years of farming experience, were identified for selection of sample participants. For the interview, a stratified sampling of participants was conducted by dividing the selected 300 farmers into separate homogenous groups or strata, and then taking a sample by simple random sampling from each stratum. The chosen sub-sample formed the stratified sample needed. This ensured adequate representation of various demographic and socio-economic factors (e.g., gender, age, education, land holding, and farming experience), which can influence perceptions of short and long-term climate variability, the associated risks, and coping strategies (Meze-Hausken, 2004; Osbahr et al., 2011; Rao et al., 2011). This process led to 60 farmers from six villages and two districts participating in this study.

One FGD was held in each district. Each FGD included twelve representatives (village leaders who had extensive experience in farming and a good extent of knowledge of their village) from the three villages per district (i.e., a total of four representatives from each village). From the KIs participants, farmers with more than 20 years of farming experience were purposely sampled to obtain in-depth information on their experience of climate variability.

Focus group discussions and key informant interviews

The aim of FGDs is to obtain a better understanding of feelings, attitudes, and perceptions of participants on a specific area of interest without pressuring individual participants to express their ideas (Morgan, 1997; Krueger and Casey, 2002; Hennink, 2007). The interaction of diverse individual experiences in the focus group allows for obtaining an in-depth understanding of similarities, i.e., a '*socially constructed collective experience*' (Morgan, 1997). FGDs were carried out before the individual in-depth interviews to discuss the issues, debate strategies, or confirm experiences more broadly (Krueger and Casey, 2002). Farmers' perceptions of historical climate patterns as far back as 20 years were assessed during FGDs. These were facilitated to create an environment in which the participants – some might not have known each other – would feel relaxed and encouraged to engage and participate. The FGDs lasted for about two hours. The views of farmers of local climate variability were illustrated using piles of stones and by breaking sticks at various sizes to represent relative quantities of historical seasonal rainfall for the year between 1992 and 2011. Farmers also classified historical seasons as 'bad', 'average', or 'good' based on the effect of the seasonal climate on maize productivity. Historical events were discussed using timelines drawn on the ground by encouraging them to recall the years with unusual climatic events (e.g., droughts and floods). Notes were taken during the interviews, and all sessions were audio-recorded to capture details to be reviewed later. Data from the FGDs were summarised according to major themes and illustrated by direct quotes, recounting events and the views of farmers.

The questions used in the KIs were the same as for the FGDs, with the exception of additional information on demographic and economic background (family size, farming experience, gender, age and education level of the household head, land-holding size, and land allocated for maize). Each interview was conducted for approximately 1.5 hours with the household head who is the main decision maker of most agricultural activities, including which crops to plant, the timing of sowing, and other activities. Therefore, the gender of household head is hypothesised to influence a series of farming decisions in response to climate variability.

3.2.5. Statistical analysis of survey data

Data were analysed using SPSS (version 20; IBM Corp, 2011). Explanation and interpretation of farmers' various opinions and views acquired through the FGDs and KIs were summarised, categorised and presented in the form of qualitative inquiry and descriptive statistics (Bryman, 2008). The results of qualitative and quantitative responses extracted from questionnaires were tabulated or presented in graphical forms. A qualitative methodology was employed to investigate farmers' perceptions and management decisions. The farmers' ratings of the long-term seasonal rainfall conditions (1999–2011) were compared to the criteria published by Ethiopia's National Meteorology Agency (NMA) for classifying seasons as 'good', 'average', or 'bad'.

Descriptive statistics were used to summarise and categorise the data, and to describe the socio-economic characteristics of the participating household. The Mann-Whitney U test was applied to assess the statistical difference between the farmers of the two study areas in regards to farming experience, gender, education level, and land holding. For the closed-ended questions, the variables were coded as nominal, ordinal, or scale data. Nominal variables of multiple response questions were presented as frequencies and percentages. For ordinal response variables, respondents were asked to rate how strongly they agreed about the accuracy of traditional forecasts and scientific seasonal forecast information using a five-point rating scale (1 = not accurate, 2 = unsure, 3 = fairly accurate, 4 = accurate, and 5= very accurate). This scale was based upon the Likert scale (Likert, 1932; Mueller, 1986) for quantifying and comparing attitudes (Marshall, 2010). The Kruskal-Wallis test was used for non-normal data to evaluate if there were any differences in how farmers perceived climate variability in terms of the frequency of good, average and bad seasons out of every ten years. The chi-square statistic was applied to test if the proportion of farmers at AJK and Bosset districts were the same in their response to indicate the most important attribute of climate-related risk factors and the key management strategies being applied in the face of climate variability.

3.3. Results

3.3.1. Characteristics of the participants

Generally, the sampled farmers at AJK and Bosset districts did not differ significantly in the characteristic features detailed in Table 3.3, except age and education level. Most of the household heads were in the age group of 30–45, with a mean of 39 years (Table 3.3). The youngest household head interviewed was 22 years old and the oldest was 70 years of age. At AJK, 80% of the respondents were male and 20% were female, while the proportions were 70% male and 30% female at Bosset (Table 3.3). For both districts, the average household size was five. The minimum number of people in a household was two and the maximum household size was 12. About 60% of the households surveyed had three to five members. This was similar for both female- and male-headed households. The total number of household heads with at least primary education (1–8 years of schooling) was 53 out of 60 respondents (88%). Nearly 80% of female farmers and 90% of male farmers interviewed at Bosset, and all famers at AJK had at least primary education. In general, younger farmers were more educated than the older farmers (data not shown). More than 70% of the farmers interviewed had more than 15 years of farming experience. The average farm size was 2.25 ha, with 20% of them holding less than 1.25 ha. Farmers with land holdings between 1.25 and 3 ha accounted for 67%, while 13% owned more than 3 ha. Around 40% of the farmers allocated more than 50% of their land holding to maize, confirming that maize is the most common food crop grown in the study districts. At AJK, female-headed households on average owned a land size 0.63 ha smaller than that of male-headed households. In contrast, female-headed households held, on average, 0.58 ha larger farms than male-headed households at Bosset.

Table 3.3: Characteristics of households surveyed in the Bosset and Adamitulu-Jido Kombolcha (AJK) districts, Ethiopia.

Characteristics	**Bosset (n=30)**				**AJK (n=30)**			
	Male		**Female**		**Male**		**Female**	
	n	**%**	**n**	**%**	**n**	**%**	**n**	**%**
Gender	21	70	9	30	24	80	6	20
Age groups								
<30 yrs.	2	7	1	3	6	20	2	7
30–45 yrs.	11	37	3	10	16	52	2	7
>45 yrs.	8	27	5	17	2	7	2	7
Average family size								
<3 family members	1	3	-	-	3	10	-	
3–5 family members	12	40	6	20	13	43	5	17
>5 family members	8	27	3	10	8	26	1	3
Education level								
No formal education	7	23	2	7	-	-	-	-
Primary education	8	27	6	20	15	50	3	10
Secondary education	6	20	1	3	9	30	3	10
Post-secondary education		-		-		-		-
Average farming experience								
<15 yrs.	4	13	1	3	8	27	1	3
15–25 yrs.	11	37	6	20	12	40	4	13
>25 yrs.	6	20	2	7	4	13	1	3
Average farm size								
<1.5 ha	10	33		-	4	13	2	7
1.5–3 ha	2	7	5	17	10	33	2	7
>3 ha	9	30	4	13	10	33	2	7
Land allocated to maize	**ha**	**%**	**ha**	**%**	**ha**	**%**	**ha**	**%**
	1.24	40	0.82	47	1.75	65	1.13	70

3.3.2. Farmer criteria used to describe past maize growing seasons

Farmers classified the seasonal climate into three groups (Table 3.4). The main criteria used to define a ‘good season’ depended on whether the rain begun early and was evenly distributed (intermittent dry-spells of less than 5–7 days) resulting in more productive crops than in an average year. A bad season was defined by the late onset of rain, when there was limited rain during the early stages of the crop, when there was a long dry-spell to prevent the crop establishing well or incidents of long dry-spells around flowering and grain filling stages of the crop significantly reducing the yield. An average season was categorised as being between a good and a bad season. Similar criteria were used by the farmers at both locations for evaluating any specific seasonal climate as being good, average, or bad. For instance, they used the same descriptive criteria to define the amount, distribution of seasonal rainfall and productivity of maize in any particular season. The other important factors identified to describe the seasonal climate were the frequency of intense rainfall events that cause floods, the incidence of long dry-spells around flowering and grain filling stages of the crop, and early cessation of seasonal rainfall.

Table 3.4: Different criteria of farmers used to classify different seasonal climatic conditions.

Location	Good season	Average season	Bad season
Bosset	High maize yield (2.5–3.0 t ha^{-1}): rainfall begins well in May-early June, poor rainfall or no dry-spell of more than 12 days after sowing, well-distributed rainfall throughout the season until late-September (e.g., rainfall with breaks of at least 5–7 days, good sunshine insolation, average temperature and no windy conditions).	Average maize yield (1.5–2.0 t ha^{-1}): rainfall begins in mid-June, or poor rainfall after the season start which may cause poor seedling establishment and/or the seasonal rainfall ends before mid-September, and/or poor distribution of rainfall with intermittent dry-spells of more than 10 days, otherwise rainfall continuous without breaks which may cause floods; and/or with much windy conditions.	Poor maize yield (0.0–0.6 t ha^{-1}): late-onset of rainfall (i.e., starting after end of June), false start of rainfall where early sown maize stands fail to establish and/or incidence of long dry-spells of more than 15 days at any stage of maize growth, or else continuous and heavy storms that cause severe flooding, especially around flowering
AJK	High maize yield (3.2–4.8 t ha^{-1}): rainfall begins well in March, poor rainfall or no dry-spell of more than 9 days after sowing, well-distributed rainfall throughout the season until mid-September (e.g., rainfall with breaks of at least 7–9 days depending on the soil type, and no windy conditions.)	Average maize yield (2.0–2.8 t ha^{-1}): rainfall begins in mid-June, or poor rainfall after the start of the season which may cause poor seedling establishment and/or early cessation of seasonal rainfall before September, and/or poor distribution of rainfall with intermittent dry-spells of more than 12 days, otherwise continuous rainfall of more than 5 days which may cause maize to turn yellowish and/or be susceptible to rust, or that may cause severe flooding; and/or with much windy conditions.	Poor maize yield (0.0–0.8 t ha^{-1}): late-onset of rainfall (i.e., starting after late June), false start of rainfall where early sown maize fails to establish, and/or incidence of long dry-spells of more than 15 days especially after sowing and/or around flowering.

3.3.3. Perceptions of climate variability and associated risk

Farmers from the two study districts gave similar ratings for cropping seasons between 1992 and 2011 in the FGDs (Table 3.5). Specifically, 25 to 45% of the seasons were rated as good, 35 to 55% as average and 20% as bad (Table 3.5). For more than 70% of the respondents, climate variability was related mainly to timing, amount, and distribution of rainfall, or a combination of these factors. While 65% of the farmers said that temperature was contributing to climate variability, 23% of the respondents said that temperature did not contribute to climate variability.

Table 3.5: Rating of seasons (1992–2011) for two districts in the Central Rift Valley of Ethiopia.

Year	Seasonal rainfall	
	Bosset	AJK
1992	Good	Good
1993	Good	Good
1994	Average	Average
1995	Bad	Bad
1996	Average	Good
1997	Bad	Bad
1998	Good	Average
1999	Average	Good
2000	Average	Good
2001	Average	Average
2002	Bad	Bad
2003	Good	Average
2004	Average	Bad
2005	Good	Good
2006	Average	Good
2007	Average	Average
2008	Average	Average
2009	Average	Average
2010	Average	Good
2011	Bad	Good

Farmers were asked to identify the frequency of occurrence of different season types out of 10 seasons (Fig 3.2). At Bosset, 35% of the seasons were rated as bad, 37% as average, and 28% as good. At AJK, around 31% were rated as bad, 50% as average, and only 24% were considered as good. The data for each district were tested for any difference in season ratings related to the demographic and socio-economic background of the household, using the Kruskal-Wallis test. Farmers' perceptions of expected frequency of a bad, average, or good season in a given 10 years were only significantly different between gender class and level of education (i.e., between primary and secondary school attendants) at AJK.

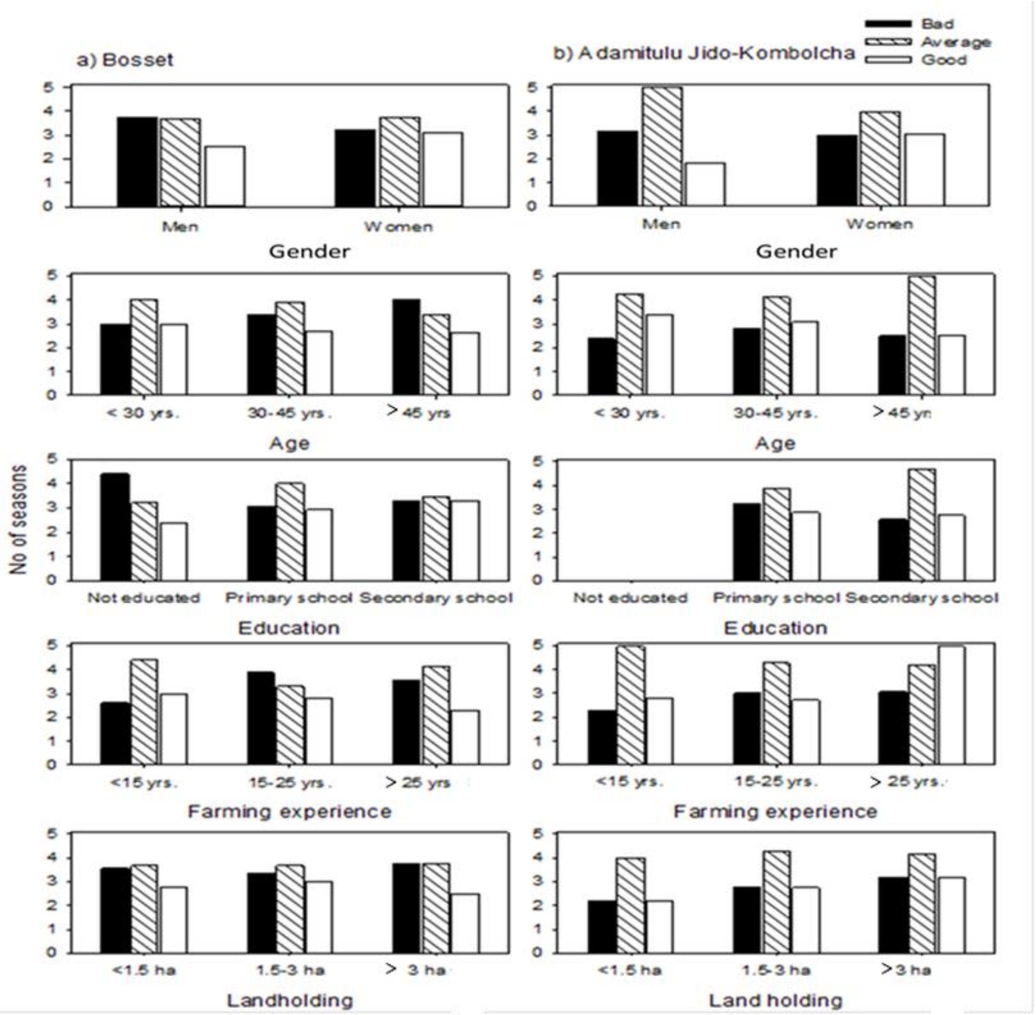


Figure 3.2: Number of good, average and bad seasons out of ten seasons as perceived by farmers. Results are grouped by gender, age, education, farm experience and land holding.

The NMA (Korecha and Sorteberg, 2013) provides a season classification based on the percent deviation of the seasonal rainfall from the long-term mean. In NMA classification, seasons with rainfall in excess of 67% of the long-term mean are classified as good, those with rainfall less than 34% of the long-term mean are classified as bad, and seasons between 34–66% of the long-term mean are classified as average. For the seasons 1999 to 2011, there was generally a good agreement between farmers' rating of 'average' or 'bad' seasons and the assessment provided by the NMA (Fig. 3.3a and 3.3b). However, for seasons which the NMA classified as good, many respondents tended to classify the seasons as average. Although the seasonal rainfall received in 2011 was above-normal, farmers at Bosset viewed the seasonal climate as bad because of frequent rainstorms that adversely affected their maize. Farmers generally considered a season as bad if the performance of crops was poor and the yield of maize was lower than the threshold limit of maize yield expected by farmers.

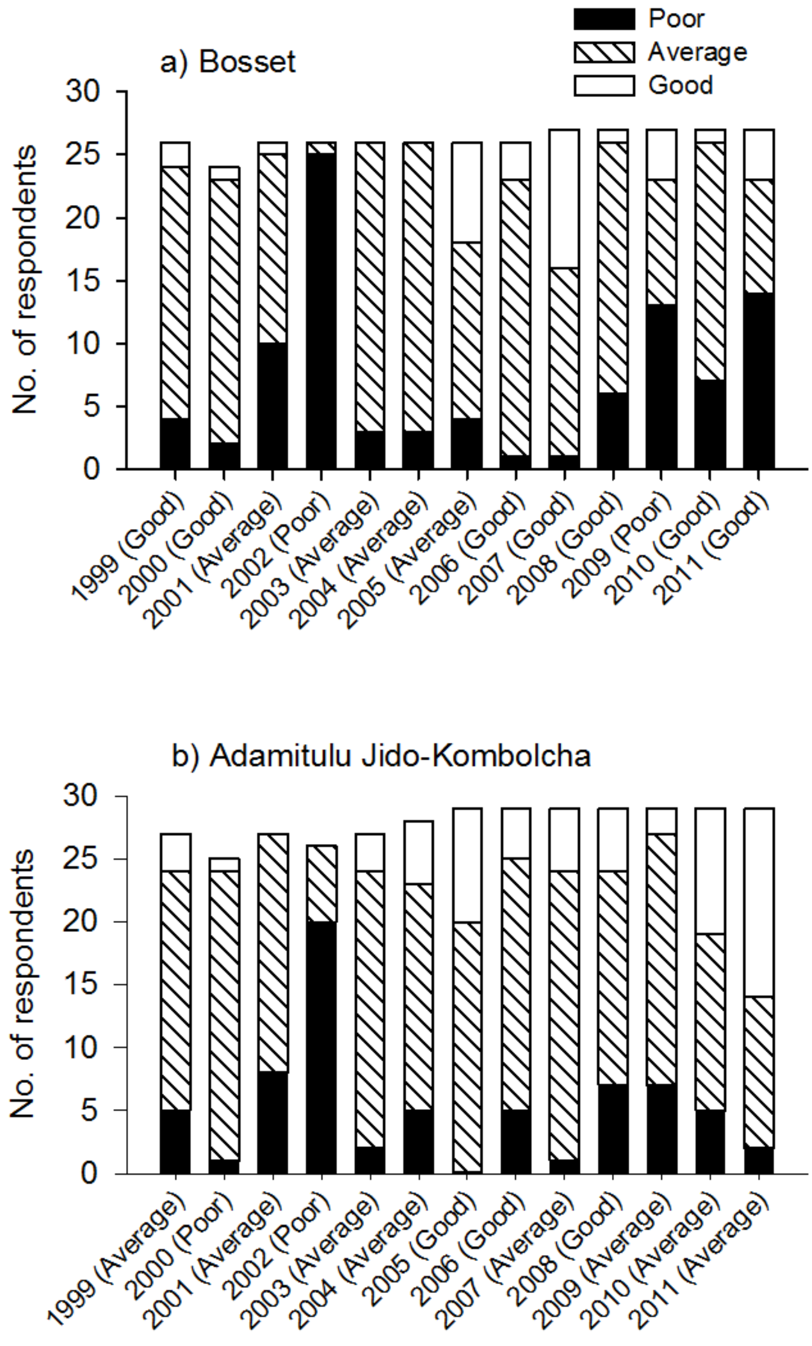


Figure 3.3: Farmers' ratings of seasonal rainfall conditions at Bosset (a) and Adamitulu Jido-Kombolcha (b). The ratings in parentheses are based on the classification of the Ethiopian National Meteorology Agency (Korecha and Sorteberg, 2013).

Farmers indicated that they would expect a maize yield of about 0–1 t ha^{-1} in bad seasons, 2.5–3 t ha^{-1} in average, and 3–5 t ha^{-1} in good seasons. This was the same in both districts. Maize yields estimated by farmers are summarised in Figure 3.4.

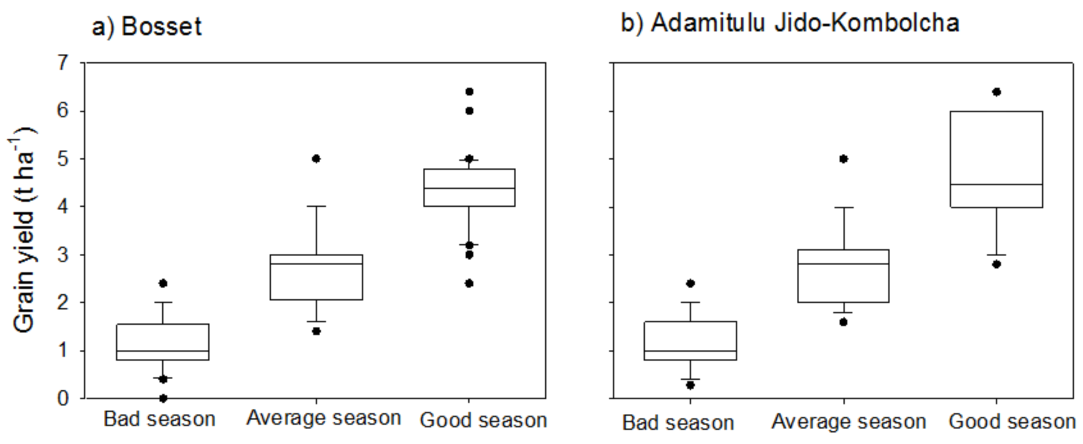


Figure 3.4: Farmer estimates of maize grain yield in bad, average, and good seasons (N=60). The boxes show the 25th, 50th (median), and 75th percentile. The whiskers show the 10th and 90th percentile, and yields greater or less than the 10th and 90th percentile are indicated by circles.

Farmers at both locations perceived the seasonal rainfall patterns as more variable and less predictable as indicated by the onset of seasonal rainfall, length of the season, and the distribution of in-season rainfall. Thus, farmers felt that the climate was increasingly erratic, with the effects of seasonal rainfall variability on maize yields worsening. Farmers from both the Bosset and AJK districts mentioned climate variability and its undesirable effects on their maize crop, as follows:

"[…] we are witnessing that inter-seasonal rainfall variability is getting much worse and it is so unpredictable…we sometimes don't know what to do". (62 years, male, Bosset)

"We are highly uncertain about the start of the season because of its irregularity […]. There were seasons when the rain started reliably. In contrast, there were seasons when the rain would not stabilise once it had started". (51 years, male, AJK)

"In some years, we experienced heavy rainstorms as well as windy conditions that adversely affected our maize crop […] while in other periods of the year, the seasonal

rainfall duration was unexpectedly short, and not enough to meet the minimum amount of water required for the maize crop as well as to harvest reasonable maize yield for sustaining our household […]". (49 years, female, AJK)

Farmers were more concerned about the start of the season within the expected sowing window, as this is critical for 'good yields'. Farmers characterised the pattern of seasonal rainfall in relation to crop production. Farmers expect the rainy season to occur between March and September for AJK and between April and September for Bosset:

"Although, the start of the season varies across years, we expect rain to start in March and to continue until mid-September". (54 years, female, AJK)

"The seasonal rain in our area starts in April […]. There is a high chance of dry-spells in between until the season ends in September". (56 years, male, Bosset)

However, farmers described that the rains between the beginning of the season and the early weeks of June were limited and unreliable, and that there was a high likelihood of a long, though varying, dry-spells, whereas the rainfall between June and August was more reliable and evenly distributed. Farmers described the highly variable nature of the timing of the onset of the rainy season by expressing how difficult it is to anticipate the reliable start of the season and how the timing of the onset of rains is less regular, as follows:

"I would not sow my maize in March unless after two to three showers of rain that sufficiently wet the soil for sowing maize. Otherwise, there might be a risk of false onset of rain". (62 years, male, AJK)

"There were a lot of occasions that I risked my seed when maize was sown before June as the maize seedlings suffered from the recurring long dry-spells". (60 years, male, Bosset)

According to farmers at AJK, the start of the season was defined by the first sowing opportunity after 1 March, while for farmers at Bosset the season would typically start after 1 April. Although farmers did not describe rainfall amounts in millimetres, farmers explained that they have their own way to quantity amounts of seasonal rainfall. They examine the soil moisture after the onset of the rains using the traditional *maresha* plough to assess the infiltration depth. Alternatively, farmers simply scrape the soil away with their hands to check if the soil is sufficiently moist for sowing. A farmer explained:

"The water getting into the soil after the onset of the rains should be enough for making the soil profile sufficiently moist, up to the depth of the maresha plough tip; so that we make sure that the seed can germinate". (64 years, male, Bosset)

The most important risk factors for maize production identified by farmers was late start of rainfall and insufficient rain early in the rainy season, which often leads to reductions of more than half of the crop yield through total crop failure compared to the yield that can be gained in good seasons. Farmers stated that once the season has started successfully (i.e., the above-defined criteria for the onset of rainfall and sowing are fulfilled), dry-spells exceeding 12–15 days in the following 30 days after sowing was the second greatest risk factor for their maize production. Farmers defined a day as being 'dry' if there was no rain at all, or the rain was too little to recharge the soil moisture. 'Dry-spell' is any consecutive number of days defined as 'dry'. It is a common experience that maize does not establish sufficiently well when there are longer dry-spells during the early growth stages. Farmers referred to the risk factor of intermittent dry-spells during the early period of the season as 'false' or 'unfaithful' rains. Farmers recalled specific years (e.g., 1995, 1997, and 2002) when the earlier sown maize failed. In these years, they lost their valuable seed, time, and energy because of post-sowing risk that resulted from scant rain or prolonged dry-spells. The following statement illustrates the perceptions of farmers:

"*We consider seasonal rain as unfaithful or false rain, if the rain once sets in but tails off at the early growth stage of the crop, resulting in very poor establishment or total failure of maize …" (56 years, male, Bosset)*

"[…] there were years when we lost all our seed because of long breaks of dry-spells after early rain […] there was a year that our crop failed due to drought and we had to receive food aid from the government". (56 years, male, Bosset)

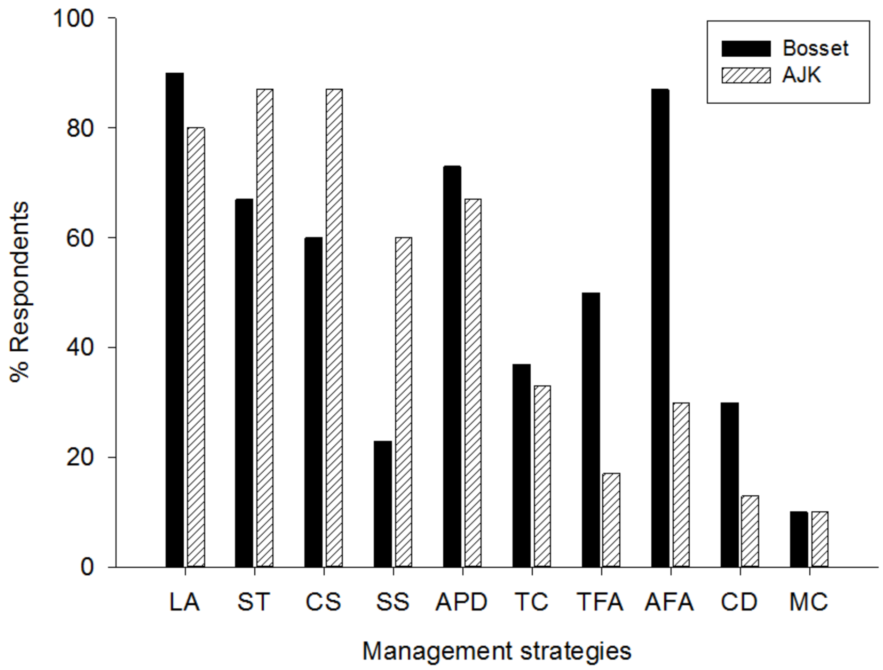
When farmers were asked to indicate the most detrimental climate risk adversely affecting their maize production, many farmers at both locations identified two climate risk factors as the most important (Table 3.6). More than 80% of the farmers rated the timing of seasonal rainfall and rainfall amount during early crop stages as the main factor in determining the quality of a particular season. A late start to the seasonal rainfall was regarded as the most detrimental risk factor for maize production. The late onset of rainfall was taken as an indicator for the seasonal rainfall being shorter in duration than expected and one in which the crop would be exposed to a high risk of terminal water stress.

Table 3.6: The importance attributed to various climatic risks that farmers identified in affecting their maize production at Bosset and Adamitulu Jido-Kombolcha (AJK).

	% of respondents				
Indicator of climate risk	**Bosset (n = 30)**		**AJK (n = 30)**		**Pearson χ2**
	Yes	**No**	**Yes**	**No**	
1. Late start of rainfall	90	10	73	27	2.78 (p = 0.09)
2. Insufficient rainfall at the start of the season	80	20	60	40	2.86 (p = 0.08)
3. Early cessation of rainfall	60	40	43	57	1.67 (p = 0.15)
4. Dry-spell around flowering	23	77	27	73	5.71 (p = 0.02)**
5. Frequent heavy rainstorms	7	93	3	97	0.09 (p = 0.05) *
6. Dry-spell after flowering	7	93	37	43	7.95 (p = 0.50)
7. Unusually high or low temperatures	3	97	7	93	0.35 (p = 0.05) *

3.3.4. Management strategies used by farmers in response to varying seasons

Farmers responded to climate variability to a certain extent by employing a set of alternative agronomic management practices for the possibility of rains arriving early or late, of rains stopping after initial rains, and the crop failing to establish. The various management strategies adopted by farmers in response to the start of the season and/or in-season rainfall conditions are presented in Figure 3.5. More than 80% of respondents identified the following management decisions as the most important: (i) the proportion of land allocated to maize, (ii) sowing time for maize and other crop types, and (iii) the maturity-type of the cultivar (Fig. 3.5).



LA	Land allocation of different crops
ST	Sowing time
CS	Cultivar selection
SS	Seed source
APD	Adjustment of plant density
TC	Type of crop to sow
TFA	Time of fertiliser application
AFA	Amount of fertiliser if applied
CD	Crop diversification
MC	Moisture conservation practices

Figure 3.5: Key management strategies applied by the farmers in response to climate variability in the Bosset and Adamitulu Jido-Kombolcha districts of Ethiopia (see text for details of the various management strategies; (N=60)).

Farmers allocated a larger portion of their land holdings to maize when the onset of the season was earlier than usual. Farmers think they would get a substantially greater yield advantage from sowing maize compared to sowing other food crops common in the area. They also prioritised their maize to be sown on fertile low-lying fields, which receive alluvial deposits and runoff from the surrounding uplands area. If the season was delayed, farmers would tend to reduce the portion of the field allocated to maize and they would opt to diversify the type of crops, which are sown at staggered timing and different fields, to minimise the crop losses and to spread farm risk.

Farmers harnessed the potential of different maturity-type cultivars that are suited to the varying timings of the rainy season onset. The different maturity-type maize cultivars may not be sown beyond a certain cut-off date to avoid water stress at critical growth-stages. Cut-off dates were at the end of April for late-maturing, early June for medium-maturing, and end of June for early-maturing cultivars. If two to three sequential wet periods did not occur before the cut-off date was reached, it was assumed that the specific cultivar could not be sown any more. If the rain stopped, or was too low after initial rains and the crop failed to establish well, farmers would sow a different cultivar suitable for the next sowing opportunity.

When the onset of the rainy season started between March and April, 30% and 60% of farmers at Bosset and AJK, respectively, preferred to sow the late maturing maize as they perceived it had a yield advantage. Farmers at AJK indicated that the onset of the rainy season in March would make them invest in late-maturing hybrid maize (BH-540 or PHB-3253), which can mature in 135–145 days. However, 40–70% of farmers perceived that there would be a high chance of a prolonged dry-spell after early rains in March or April, which might cause germinated seeds or seedlings to die. In turn, those farmers would sow medium-maturing maize cultivars (130 day) in early June. If the rain was still delayed up until the end of June, they would sow early-maturing maize cultivars (<110) to fit the shorter growing season period. Farmers said that they did not sow maize after the end of June. For those seasons with a late onset of rain after the end of June, farmers would opt to grow other extra-early duration crop species such as wheat, common bean or tef. Farmers described the relationship between the timing of the onset of the rainy season and the maize cultivar or other crop species chosen as follows:

"I tend to re-plough the field and re-sow maize if the first sown maize failed to establish because of low seasonal rainfall at early stage of the crop; or we sow an extra-early maize or quick-maturing crop such as common bean that could mature within the remaining rainy season". (69 years, male, AJK)

"*The decision of sowing of any particular cultivar depends on the timing of the seasonal rain…cultivars of different maturity groups have different cut-off dates, and a cultivar will not be sown if the date passes…" (45 years, male, Bosset)*

Seasonal conditions also dictate fertiliser management. Many farmers did not apply commercial fertilisers. Key management decisions of those who used N fertiliser was how much N fertiliser to be top-dressed at the 5–6 leaf stage, which is conditionally determined depending on how well the maize crop is established, and the expected potential of the remaining seasonal rainfall on the performance and final harvest of the crop.

"The onset of seasonal rainfall and the rainfall distribution early in the cropping season is the main factor in making decisions such as whether we need to apply N or not– if we happen to apply–we decided on how much N fertiliser to apply on our maize crop …". (48 years, male, AJK)

From the 60 farmers interviewed, only 10% of the farmers applied both di-ammonium phosphate (DAP)and urea at Bosset and AJK. Around 27% of the farmers at AJK applied only DAP while 17% of farmers at Bosset applied only urea. In contrast, more than 50% of farmers did not apply commercial fertiliser at all. Farmers commonly apply fertiliser at rates of approximately 60–100 kg ha^{-1} DAP and 40–65 kg ha^{-1} urea. As a fertility amelioration strategy, more than 80% of farmers used organic fertilisers as they are cheaper. Farmers preferably applied organic inputs close to their homestead. Around 17% of respondents at Bosset and 20% at AJK applied dry farmyard manure at a medium-distance (500–700 m from homestead) and in remote fields (700–1250 m) prior to land preparation. Those farmers who did not apply commercial fertiliser think that their soil is fertile enough and they did not expect any additional yield advantage from commercial fertiliser use. They stated that a maize yield comparable with the field receiving commercial fertiliser could be achieved as long as the rain is adequate and fairly-well distributed.

Most farmers adjust some agronomic practices such as planting density as they use higher seed rates at sowing to ensure adequate plant stands if the rains at the initial stage of the season is scanty and intermittent. However, they reduce the plant density of maize around 4–5 weeks after sowing when they are practicing *shilshalo* in order to better match to the anticipated seasonal rainfall potential. Only 10% of the respondents at the study areas mentioned they are using tied-ridging which is typically ridging the soil to heights of 20 cm or more either before or after sowing by cross-tying the furrows at distances of 2 m or more to form a series of micro-catchment basins in the field. It is an *in situ* water harvesting technique that is promoted by the extension workers in the study areas. On the other hand, all farmers use a traditional *in situ* water conservation practice called *shilshalo*, as a means of reducing water losses to runoff and increasing stored soil water.

3.3.5. Awareness and use of seasonal climate forecast information

Farmers have long used indigenous knowledge to predict the weather in the upcoming season. Indigenous forecasting methods combine experience of historical weather patterns (e.g., temperature, wind direction, rainfall pattern in the off-season, cloud formation on the mountains), diverse indicators including the state of flora (e.g., trees such as *Acacia tortilis*) and fauna (e.g., birds such as *Bucorvus abyssinicus*), local weather patterns, and astrology (e.g., star constellations, size and shape of moon). In FGDs, farmers mentioned the following indicators:

"[…] we know the approaching season is going to be good if the acacia trees blossom early"

"*The prevalence of 'Awlonifas' [whirlwinds] that stir up and lift a vast quantity of dust and go straight upward early in January and February is an indicator of early start of rain in March"*

"The appearance of bees coming from east to west marks the start of the rainy season…"

"Wind blowing prior to the rainy season from west to east and from north to south, is considered to bring a lot of moisture and a good rainy season".

"Low cloud perching on top of the highest Bosset Mountain will bring about large amounts of rain"

"If the sky remains clear and very low temperature persists at night just before the upcoming season, we anticipate a high risk of drought"

Although most farmers were consulting community elders and religious leaders to read and interpret the traditional indicators, they were also using their own indigenous knowledge to predict what the upcoming season might bring. Farmers who only used indigenous forecasting methods had much more faith in a God controlling nature than they did in science-based forecasts.

Individual interviews revealed that 80% of the farmers use a three-month seasonal outlook issued by the NMA before the beginning of the farming season. Many combined this information with traditional forecasts based on the knowledge of local indicators (Fig. 3.6). Around 15% of the farmers rely on indigenous knowledge to foretell the seasonal climate conditions. Overall, the mean response to questions about the accuracy of operational forecasts from the NMA was 2.9 (s.e. = 0.13) and traditional methods was 2.2 (s.e. = 0.12) while the response about the accuracy of the information was 3.5 (s.e = 0.14) when the forecast information from NMS and traditional methods was combined. In a Likert scale of 1–5, a mean score of greater than 2.5 for the accuracy of the forecasts is considered to be good as there is a high level of agreement among most respondents. This result reflects that 79% of the participants perceived the NMA forecasts as reliable in identifying whether the forthcoming season is going to be below normal, or normal to above normal, while 92% trust the NMA forecasts if combined with indigenous forecasting methods. Farmers explained that climate information for an upcoming season is useful in guiding their management decisions. Generally, all participants used seasonal forecast information, regardless of the type of seasonal forecast. Farmers strongly emphasised the importance of credible, seasonal-specific climate forecasting information to guide decision-making.

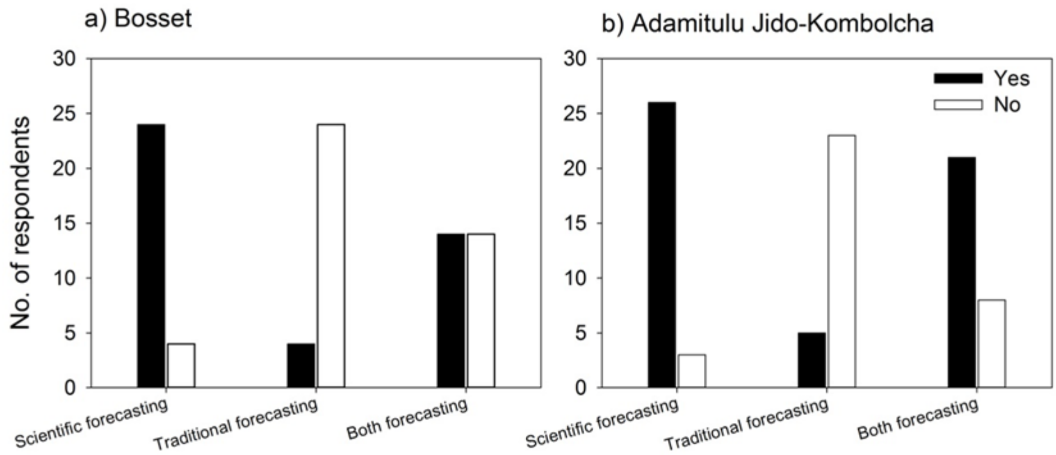


Figure 3.6: Type of climate forecasts used in making farming decisions (N=60).

3.4. Discussion

3.4.1. Perception of climate variability and risk

The focus of this study was to gain better insights on how farmers perceive climate variability and use their knowledge of these impacts in managing risks in maize-based cropping systems. Generally, farmers perceived and described climate variability and risk in relation to maize growth and yield (Tables 3.4 and 3.5; Fig. 3.4). Of all the rainfall characteristics, total amount of seasonal rainfall was rated less critical than variations in the timing of the onset and the end of the rainy season, as well as dry-spells during the growing season (Table 3.6). Farmers shared a strong sense of what was a bad, average, and good season in the past 20 years (Table 3.5). In particular, almost all interviewed farmers recollected extreme climatic events that occurred during the past 20 years, and described 1995, 1997, and 2002 as the 'worst drought years in human memory'. This can be expected considering the high impact these events had on the productivity of crops (Meze-Hausken, 2004; Orlove et al., 2010; Rao et al., 2011). Many studies have shown that farmers are very good at recollecting extreme climatic events, which had a significant impact on their family life (Mertz et al., 2009; Meze-Hausken, 2004; Osbahr et al., 2011; Moyo et al., 2012). The similarity in criteria used by farmers to distinguish seasons demonstrated their collective memory of past climatic conditions. These common perceptions of historical climatic conditions and farmers' criteria to define the various seasonal climate showed that the participating farmers possess a good understanding of the local climate (Coe and Stern, 2011; Rao et al., 2011).

Common perceptions of, and criteria to describe climatic conditions arise from socially constructed knowledge and experiences, which are shared by many farmers (Stehr and von Storch, 1995; Stehr, 1997). Furthermore, the maize yields expected in favourable, average, or unfavourable seasons were nearly the same for most farmers involved in the study (Fig. 3.4), and within the range of maize yields estimated by other farmers in the CRV of Ethiopia (Dimes et al., 2011; Kassie et al., 2013a). There was mostly agreement between farmers' ratings of season-types and the official classification published by the NMA. However, there were also differences (Fig. 3.3). Given the importance of the temporal distribution of rainfall for crop growth and yield, meteorological and agricultural classifications of season types often produce different results (Meze-Hausken, 2004). Farmers' perceptions of seasonal climate variability and risk are more attuned to the pattern of seasonal rainfall in affecting crop growth and yield, while meteorological definitions of rainfall anomalies do not consider the seasonal rainfall supply in relation to crop demand (Wilhite and Glantz 1985; Osbahr et al., 2011).

Farmers in the study areas rely on local knowledge, like many smallholder farmers in Africa, to monitor seasons (Roncoli et al., 2002; Ziervogel and Downing, 2004). The historical pattern, local weather observation, and other indicators allow farmers to form expectations of what the rainfall conditions are likely to be in the season ahead. These observations are particularly important prior to the commencement of sowing as many of the decisions are based on the timing of the onset of the rains (sowing time, cultivar choice, the portion of the land allocated to maize and the type of other crop species). Once the season starts, they also monitor the unfolding season to make the necessary adjustments in management decisions, such as how much N fertiliser to apply or if they need to re-sow an early maturing cultivar depending on how well the early-sown maize is established. Although farmers were positive about the quality of forecasts issued by the NMA, many respondents raised the concern that the forecasts were not detailed and specific enough for their farming enterprise. Farmers would like to receive skilful forecasts about the *Belg* (March–May) and *Kiremt* (June–September) season, including information about timing of the onset of the rainy season and reliability of rainfall (i.e., risk of prolonged dry-spells) at their location. The NMA forecasts for the *Belg* and *Kiremt* season are probabilistic – expressed as the chance of being 'above normal', 'below normal' or 'near normal'– and issued for large areas classified as homogenous zones (NMSA, 1996; Korecha, 1999, 2002). The rainfall in the region is spatially highly variable especially during the *Belg* rainy season. This means that forecasting *Belg* rain is more difficult compared to *Kiremt* rain (NMSA, 1996). The forecasts often lack concise, localised information on climatic variations. Forecasts may be improved by integrating indigenous knowledge, which is highly localised and often includes practical advice on management measures in light of the forecast conditions (Kihupi et al., 2003; Roncoli, 2006).

Since the early 1990s, farmers have noticed that the onset and distribution of early seasonal rainfall has become less reliable and more variable. Many farmers mentioned that the *Belg* rain has become less reliable as indicated by a greater risk for a false start of the season and intermittent dry-spells. As a consequence, farmers fear to sow maize during this period. Analysing the crop water requirement of early-maturing maize (<110–130 days from sowing to maturity), Diga (2005) found that water supply is insufficient to meet crop demand in 60% of seasons, often causing total crop failures. On the other hand, *Kiremt* rainfall is typically adequate for the critical crop growth stages between flowering and physiological maturity though the crop may still face water stress during early *Kiremt*, i.e., June. Comparing the seasonal variability of rainfall in the region, *Belg* rainfall is more variable than the *Kiremt* rainfall, as indicated by the higher coefficient of variation (CV%) of *Belg* rain than that of the *Kiremt* rain (CV% 45–48 versus CV% 21–30). The *Belg* rain is affected by a higher probability of dry-spells than the *Kiremt* as the *Belg* season is influenced much more by cyclonic activity than the *Kiremt* season (Seleshi and Camberlin, 2006). The variability of *Belg* rain in the recent two decades (CV% 40–45) is lower than the long-term *Belg* rain (CV% 45–48) for the two study areas. Detailed analysis of long-term daily and monthly records from the sixteen sites included in the study area has shown no major detectable change in the *Belg* rainfall amount during the past three to four decades. However, the number of rainy days and the length of the growing season in the *Belg* season showed a decreasing trend over time (Kassie et al., 2013b; Getachew and Tesfaye, 2015). The trend of shortening in the growing season is strongly associated with the late starting trend in the onset date for the *Belg* rain (Kassie et al., 2013b). The high inter-annual variability of the timing of the onset of the *Belg* rains at Melkassa and Adamitulu, implies that rainfall patterns may have permanently changed (Kassie et al., 2013b). As uncertainty of the growing season is one of the main challenges for rain-fed crop production, detailed analysis of the reliability of the *Belg* growing season is important for determining whether the season is suitable for growing food crops, while investigating the likely risk associated with different sowing dates and the type of crops and cultivars choice when there is an early start of rain during *Belg* season.

3.4.2. Farmers' management strategies

In this study, many farmers altered agronomic decisions in response to the actual and expected seasonal rainfall to manage climate variability (Table 3.4; Fig. 3.4). However, not all farmers respond in the same way. In general, a maize-based system is the dominant crop production system in the semi-arid CRV of Ethiopia (Biazin and Stroosnijder, 2012). However, farmers diversify their cropping practices both in space and time by sowing different types of crops at various times and fields as an assurance to minimising the risk of crop failure and to spread farm risk (Kassie et al., 2013a).

The most crucial management decisions are arguably made at sowing and focus on what crop or cultivar type to sow which has implications for potential to capture the flush of soil N that comes with the first rains and to achieve early food security (Weber, 1995; Jagtap and Abamu, 2003). If the onset of rains is early, farmers are likely to allocate a significant portion of their land to maize, as it is the dominant staple crop for food security and supplies crop residues for animal fodder. It is general practice in most areas of the CRV of Ethiopia to sow at the onset of rainfall in the *Belg* season, although farmers know that there is the risk of post-sowing dry-spells of varying length that can cause significant crop damage and they often need to re-sow. Farmers, who are losing confidence in the reliability of the *Belg* rains and in their ability to predict them, will wait until the *Kiremt* rains settle in. Despite the fact that many farmers in the CRV aim to maximise grain and biomass yield by sowing late-maturing maize cultivars if *Belg* rains start early, there is only a modest effort directed towards breeding drought tolerant, late-maturing cultivars suitable for early sowing under *Belg* seasonal conditions, which results in limited availability of improved seeds. Breeding efforts are more directed towards the development of early- to medium-maturing cultivars and many of the released cultivars fit the length of the *Kiremt* season (Mohammed and Mulatu, 1993; Bogale et al., 2011) with agronomists simply recommending a fixed sowing window for the promoted maize cultivars. This sowing window is to be in June, with sowing to be carried out once rainfall is effective in wetting the soil. The effect of varying sowing dates, including farmers' sowing rules for various timing of onset of rains, on the yield of maize cultivars with differing maturities has not been properly evaluated. In the CRV region, farmers are practicing flexible sowing decisions based on the onset time of the rainfall season; however, crop failure due to false starts of the rainfall season is a common risk (Kassie et al., 2013a). In this respect, therefore, farmers could make informed decisions, if the risk and crop yield probabilities associated with different sowing decisions is understood and the results can be properly communicated by advisors and extension services in aiding farmers' decision making (Jagtap and Abamu, 2003).

In this study, few farmers applied mineral fertiliser N at sub-optimal rates (20 and 38 kg N ha^{-1}) but many did not apply fertiliser N at all. According to a survey conducted across 6500 farmers' fields in the CRV of Ethiopia, around 78% of the maize fields did not receive any kind of mineral fertiliser (Getnet et al., 2016). Soil fertility in the CRV is inherently low (Biazin and Stroosnijder, 2012) and this is aggravated by nutrient mining associated with continuous cropping and limited applications of inorganic and/or organic fertilisers (Abegaz and van Keulen, 2009; Biazin and Stroosnijder, 2012). Getnet et al. (2015), who sampled a large number of fields in the CRV of Ethiopia, reported that farmers applied N fertiliser at rates as low as 2.6–16.5 kg N ha^{-1}. This is much lower than the 41–64 kg N ha^{-1} recommended by research/extension for the region (Debelle et al., 2011; Kassie et al., 2014). Thus, the low amount of N applied by some farmers in this study is the main cause for the negative soil nutrient balances (Haileslassie et al., 2005; Abegaz and van Keulen, 2009). Therefore, applying the required amount of fertilisers as well as improving the limiting resource (i.e., water and nutrient) use efficiency, are key pathways for improving the soil fertility and sustainable intensification of the maize system in the CRV of Ethiopia.

The fertiliser recommendation in Ethiopia, like many African countries (Okalebo et al., 2006; Xu et al., 2009; Goujard et al., 2011), is similar across different sections of the country regardless of the spatial heterogeneity of the soil or the local needs or the socio-economic circumstances (Stepanek, 1999). Therefore, the respondents in the study area were deterred from using fertiliser because of its high cost and/or risk of a yield response insufficient to recoup the fertiliser investment. Similar to many farmers in semi-arid regions of Africa, the interviewed farmers were risk-averse decision-makers applying N fertiliser conservatively as the return from an investment into fertiliser is uncertain due to large fluctuations in crop yields (Keating et al., 1991; Cooper et al., 2008; Dimes, 2011; Roxburgh and Rodriguez, 2016). However, around 38% of the respondents in the study area assumed that their fields were sufficiently fertile or non-responsive at all and that there would be no yield advantage from applications of commercial N fertiliser. The yield differences observed between fertilised and unfertilised fields at many sites in the CRV of Ethiopia are often marginal (Getnet et al., 2016), and farmers cannot fully observe a crop response to the fertiliser application. Poor agronomic management such as untimely sowing, use of low-yielding cultivars, sub-optimal plant density and poor weed control are important factors for poor crop responses to fertiliser that are observed on-farm (Kassie et al., 2014). In such environments, utilising N resources might be inefficient. As a result, widespread use of N fertiliser cannot be expected since it will not necessarily overcome low production and profitability, and it may even cause high production risk in smallholder farms (Roxburgh and Rodriguez, 2016). Another plausible reason for the lack of interest of the interviewed farmers in applying mineral fertiliser might be related to the degraded and poorly responsive nature of the local soil. On such soils, a large investment to improve levels of soil organic carbon is required before a crop response to fertiliser can be observed (Tittonell and Giller, 2013). Effective design of fertiliser recommendations should target specific soil fertility niches depending on their response to various nutrients (Tittonell et al., 2005, 2007b). The significant number of interviewed farmers who perceived their soils as being fertile is attributable to low awareness of the productivity benefits from using fertiliser management and possibly a limited understanding of soil fertility management, including amelioration of degraded soils (Adimassu, 2013). Therefore, researchers should closely collaborate with extension officers for capacitating them to assist smallholder farmers with a provision of effective recommendations and suitable extension advice that is locally relevant (Twomlow et al., 2010; Otsuka et al., 2011).

One way of achieving substantial yield improvements would be to improve those aspects of system management, as discussed above, that limit or prevent crop responses to fertiliser inputs to maximise the nutrient use efficiency (Tittonell and Giller, 2013; Kassie et al., 2014; Getnet et al., 2016). Therefore, a feasible pathway to sustainable intensification of maize production has to pursue a stepping stone approach. Firstly, simple and less-costly agronomic recommendations need to be promoted to small holder farmers that enable them to achieve better yields before farmers can be encouraged to adopt complex and expensive technological interventions (Roxburgh and Rodriguez, 2016).

3.5. Conclusion

Farmers perceived the current climate, particularly seasonal rainfall patterns, as more variable and less predictable. Farmers' perceptions of the seasonal climate depend on how it affects the performance of their crop production and livelihoods of their farm households. In response to the actual and expected seasonal rainfall, farmers are employing various agronomic strategies in managing climate variability, and these agronomic decisions are conditioned upon the seasonal rainfall pattern, particularly onset of rains and early prospect of the opening rain. If farmers are to make informed management decisions, research and extension provisions should have to integrate *ex-ante* management options that suit farmers' local practices, production objectives and socio-economic niche under varying prospects of the seasonal rainfall pattern. Understanding of farmers' perceptions of climate variability and risk is valuable for informing research and extension services enabling them to deliver best-fit recommendations that are adaptable to smallholder farmers who are operating in the face of climate risk and uncertainty. As farmers' perceptions of seasonal climate variability and risk are more attuned to the seasonal rainfall pattern in affecting their maize production, objective assessment of climate variability and risk would be required before utilising such farmer-based assessments of climate variability as the sole basis for future research, extension and development efforts in targeting the appropriate interventions in the region. Alternatively, modelling and simulation are powerful analyses for answering whether farmers' perceived climate and associated risk is due to their practice or not. Moreover, a modelling approach can deliver a more comprehensive analysis of the inter-seasonal variations in yield which may be affected by the complex interactions between a range of management decision options, seasonal rainfall pattern, and availability of the limiting resources (i.e., water and nutrient). Engaging farmers in the research process and using crop simulation models as a powerful research and decision tool provides useful information for discussion with the farmers and their advisors. In turn, adaptable interventions for smallholder farmers within the context of their socio-cultural behaviour, financial means, risk preference and technical capacity, along with other influencing factors can be determined.

Chapter 4 Maize (*Zea mays* L.) productivity as influenced by sowing date and nitrogen fertiliser rate in the Central Rift Valley of Ethiopia: A dataset for applying a crop model of maize growth and development

Abstract

Agronomic and physiological responses of two maize (*Zea mays* L.) cultivars to two sowing dates and two contrasting N fertiliser rates were assessed at Melkassa, Central Rift Valley of Ethiopia. The agronomic data presented here are a prerequisite for parameterising a crop model of maize growth and development for subsequent scenario analyses of sowing date and fertiliser rate effects on maize productivity under a wide range of rainfall conditions in dryland environments of Ethiopia. Late-sown maize received 42% less rainfall between sowing and silking than the earlier-sown crop resulting in a grain yield reduction of about 30% across N rates and cultivars (3.9 vs. 2.7 t ha^{-1}). Sowing date by N rate interactions were significant for the number of days required from sowing to tasseling ($p < 0.001$) and silking ($p = 0.009$). Without N application (0 kg N ha^{-1}), tasseling occurred three days later when maize was sown earlier, and two days later when sown late, both compared to the treatments fertilised with 100 kg N ha^{-1}. Similarly, silking was delayed by two days in the early-sown unfertilised crop but not in the late-sown crop. Compared to unfertilised maize, the application of 100 kg N ha^{-1} increased yield by around 70% (2.9 vs. 4.9 t ha^{-1}) in the earlier-sown crop and 30% (2.4 vs. 3.1 t ha^{-1}) in the late-sown crop (sowing date by N fertiliser rate interaction was significant at $p < 0.001$). Across sowing dates, the application of N fertiliser increased the total above-ground biomass by 50% ($p < 0.001$), and the maximum leaf area index by 32% ($p < 0.001$). Harvest index was not affected by sowing date and N application treatments. Over the growing season, application of fertiliser N increased the rate and amount of soil water extracted by maize when compared to the unfertilised treatment and, in turn, led to increase of maize water productivity in the order of 8 to 55% irrespective of the sowing date.

4.1. Introduction

In the semi-arid region of the Central Rift Valley (CRV) Ethiopia, soil moisture and nitrogen (N) are the key resources that interact in complex ways to limit crop growth and yield (Biazin and Stroosnijder, 2012). The seasonal rainfall in the semi-arid region is highly variable, and so too are the yield responses to various agronomic management regimes and application of N fertiliser input (Muchow, 1990). In farming systems having highly variable climate and edaphic conditions, farmers require reliable information regarding the production level and risk associated with key agronomic management factors, such as sowing time and use of N fertiliser input in order to support farmers make informed decisions that can enhance their crop yields or profits in situations confronted with risks associated with seasonal climate uncertainties (Ati et al., 2002). As a consequence, the large on-farm yield gap can subsequently be narrowed (Muchow et al., 1991; Shamudzarira and Robertson, 2002).

In such farming systems, however, field experiments to examine the effect of various management decision options on the crop yields or profitability remain to be a challenge as the wide range of possible system responses cannot be captured in a limited number of experimental seasons and sites (e.g., Dixit et al., 2011; Stern and Cooper, 2011). For using crop models however, one needs to conduct detailed field experiments in order to collect empirical data on crop growth and development responses, along with carefully measured soil and weather data at the experimental site. Comprehensive datasets can serve as essential inputs to models only when they are parameterised and tested. Therefore, field experiments are a requisite for measuring the range of high quality site-specific data on weather, cultivar, soil characteristics and management information from which the relevant input-parameters are generated that will enable adaption of the crop model to the local crop cultivars and environmental conditions (e.g., soil types and weather conditions). The derived parameters for modelling the relevant soil and crop processes need to be accurate in order to gain a good overall agreement between the simulated and observed values (Hunt and Boote, 1998). A well-parameterised crop model can be regarded as reliable after testing its capability in reproducing how a real crop growing under specific environment and management conditions would perform (Bationo et al., 2012; Folberth et al., 2012).

In order to apply a crop model, one needs to be confident that the model is robust and credible in simulating the key crop and soil processes well enough as a consequence of variations in seasonal climate, soil characteristics and management regimes (Hunt and Boote, 1998; Bationo et al., 2012; Boote et al., 2015). Such models can capture the most important bio-physical (plant growth and development, soil water balance) and chemical (e.g., N and carbon) processes in cropping systems (Wang et al., 2002; Delve et al., 2009; Craufurd et al., 2013; Moeller et al., 2014). That means, crop models must respond to differences in local weather conditions, soil characteristics, crop management practices and genetics to enable researchers to extrapolate various research results from specific experiments to other soil and weather conditions (Xiong et al., 2008; Ncube et al., 2010; Bationo et. al., 2012). As a result, they can serve as research or decision support tools to allow researchers, extension advisors or decision-makers to be more efficient in assessing various management options and providing a broad range of potential solutions that can suit to farmers with varying levels of resources, farming experiences and risk preferences (Shamudzarira and Robertson, 2002; Dimes et al., 2003).

The Agricultural Production Systems sIMulator (APSIM) is a reliable decision support tool for assessing crop responses and estimating the associated production level and risk as a consequence of the interactive effects of soil, weather and management factors that affect crop yield (Keating et al., 2003). A field experiment was conducted with the aim of generating the relevant datasets that are required for the APSIM model before it can be successfully applied for modelling the maize (*Zea mays* L.) system under the local environmental conditions (Hunt and Boote, 1998; Bationo et al., 2012). Therefore, APSIM needs to be parameterised and tested with the datasets observed in the field experiments in which measurements are made to generate all of the essential cultivar- and soil-related parameters, using data of daily weather, soil and crop growth responses, along with initial soil condition and management inputs. In doing so, these specific crop- and soil-related parameters can provide the inputs needed in the model so that it can be adapted to the local cultivar and environmental conditions before using the model for simulating scenarios. Therefore, a field experiment at Melkassa in the CRV of Ethiopia was setup for determining crop growth, development and grain yields of two locally cultivated maize cultivars along with soil water dynamics and water productivity of the maize crop as influenced by the local environment and management factors. The output from this experiment was used to generate and document the essential field data to be used as input for APSIM-Maize. Subsequently, the APSIM-Maize model was applied to assess crop responses to alternative management decision options (Keating et al., 2003). The specific objectives of this study were to: (i) evaluate the responses of two locally adapted maize cultivars to contrasting sowing dates and N fertiliser application rates; and (ii) obtain critically essential crop and soil data for testing the capacity of the APSIM model in simulating the response of the locally adapted maize cultivar, *Melkassa-2*, to contrasting sowing dates and rates of N fertiliser.

4.2. Materials and Methods

4.2.1. Site Description

A field experiment was conducted in 2012 at Melkassa Agricultural Research Centre in the CRV of Ethiopia (8º24' N, 39º12' E, 1550 m elevation). The location has a tropical semi-arid climate with a weakly bi-modal rainfall distribution, an average annual rainfall of 820 mm, and an average annual temperature of 21.2°C (1977–2012) (Fig. 4.1). The annual potential evapotranspiration (ETo) is 2711 mm. The average June to September rainfall, which coincides with the maize growing season, is 555 mm (ETo = 735 mm).

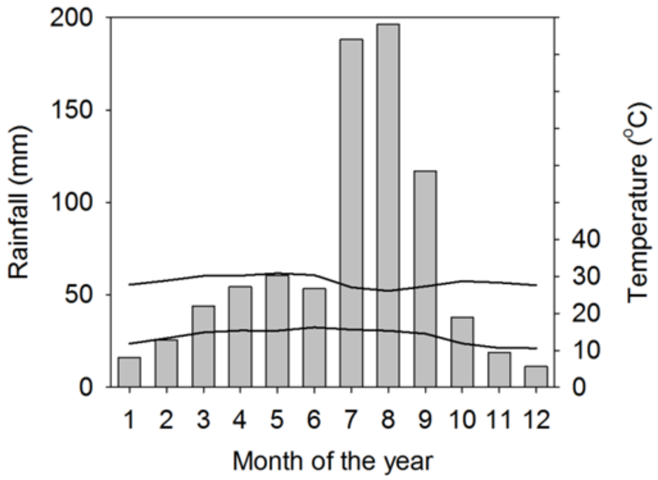


Figure 4.1: Climate at Melkassa, Ethiopia (1977–2012): mean monthly rainfall (bars) and mean monthly maximum and minimum temperatures (–). Maize is grown from March until September.

The experimental soil was a calcareous clay loam of volcanic parent material classified as a Typic Haplustand (Mesfin et al., 2009) with a maximum rooting depth of around 1.2 m. The terrain had a slope of only about 0.02 m m^{-1}. The soil had a clay loam texture, with a bulk density of about 1 g cm^{-3} throughout the soil profile (Table 4.1). The pH ranged from 7.8–7.9, which is within the optimum range for the availability of major nutrients. The percentage organic carbon (OC%), total N and P contents were greatest in the uppermost soil layer and decreased gradually with soil depth. The OC% decreased from 1.29% in the surface layer to 0.42% at 0.9–1.2 m depth. Extractable P in the surface layer (13.6 mg kg^{-1}) was in the medium range for plant availability (Olsen et al., 1982). The C: N ratio ranged from 9–11 over the profile.

Table 4.1: Physical and chemical properties of the experimental soil measured prior to the commencement of the maize experiment. One standard error of mean (+/-) is given in parentheses.

Parameter	Depth (m)				
	0–0.15	0.15–0.3	0.3–0.6	0.6–0.9	0.9–1.2
Organic C (%)	1.29 (0.02)	0.98 (0.03)	0.48 (0.03)	0.44 (0.02)	0.42 (02)
Total N (%)	0.13 (0.01)	0.11 (0.01)	0.05 (0.01)	0.04 (0.01)	0.04 (0.01)
Soil C/N ratio	9.92	8.90	9.60	11.00	10.50
pH (1:5 H_2O)	7.8 (0.2)	7.80 (0.3)	7.9 (0.2)	7.9 (0.02)	7.9 (0.2)
EC (dS m^{-1})	0.026 (0.001)	0.026 (0.001)	0.018 (0.001)	0.016 (0.001)	0.016 (0.001)
Olsen P (mg kg^{-1})	13.6 (0.4)	8.40 (0.3)	4.4 (0.3)	3.2 (0.2)	3.2 (0.2)
Sand (%)	30	32	31	28	28
Silt (%)	40	40	42	42	44
Clay (%)	30	28	27	30	28
Bulk density (g cm^{-3})	1.09	1.01	1.09	1.06	1.06

4.2.2. Experimental Design

The experiment was laid out in a randomised complete block split-plot design with three replications. The replications were arranged in blocks from east to west and separated by an alley of 2 m width. Sowing date treatments (two factor-levels) were randomly assigned to the main plots. Maize cultivar and N fertiliser treatments (two factor-levels each) were randomly allocated to the sub-plots (96 m^2) within the main plots (384 m^2). Each sub-plot had eight rows of plants. To minimise edge effects, the two outer rows on either side of the plot and 1.5 m at each end were excluded from sampling.

4.2.3. Crop agronomy

Two local maize cultivars, *Melkassa-2* and *Melkassa-3,* were sown on land previously cropped with common bean (*Phaseolus vulgaris* L.). These cultivars were bred at the Melkassa Agricultural Research Centre and are described as drought tolerant and medium in maturity. On average, *Melkassa-2* requires 130 days, and *Melkassa-3* requires 125 days from sowing to physiological maturity at 1500 m elevation (Bogale et al., 2011). *Melkassa-2* was released for its superior grain yield, and disease resistance while *Melkassa-3* was released based on breeder evaluation as well as farmer preference for agronomic attributes such as cob size, vigorous growth, high biomass production, and grain yield. Both cultivars are widely grown by smallholder farmers.

Prior to sowing, the soil was ploughed to a depth of 0.2 m using a mouldboard plough on 27 May 2012, and smoothed with a disc-plough on 5 June 2012 and a spring-tooth harrow on 18 June 2012. Subsequently, ridges spaced at 0.75 m and of about 0.35 m height were formed using a tractor-mounted ridger. The seeds were treated with fungicide (Thiram®, 0.25% (w/w) per kg) to prevent seedling pathogens. Weeds were controlled by inter-row cultivation and hand weeding as deemed necessary to maintain a weed-free environment.

Maize was hand-sown on 6 July 2012 (sowing date 1, SD1) and on 20 July 2012 (sowing date 2, SD2). Two seeds were sown into the furrow at a depth of 0.06 m with inter- and intra-row spacings of 0.75 m and 0.20 m, respectively. Maize plants were thinned to leave one plant per hole at two weeks after emergence to establish a uniform plant density of approximately 6.7 plants m^{-2}. N fertiliser was applied as urea at rates of 100 kg N ha^{-1} (N100) and 0 kg N ha^{-1} (N0). In the N100 treatment, 50 kg N ha^{-1} was side-dressed at sowing, and an additional 50 kg N ha^{-1} was applied as a top-dress application during cultivation four weeks after sowing, i.e., on 2 August 2012 for the SD1 treatment, and on 16 August 2012 for the SD2 treatment. The N100 treatment is double the rate recommended by extension services (Reddy and Georgis, 1993). No N fertiliser was applied in the N0 treatment, which represents the management practiced by most farmers in the CRV. Other nutrients applied at sowing were P (20 kg P ha^{-1}; side-dressed as single super phosphate) and potassium (25 kg K ha^{-1}; broadcast uniformly across plots as muriate of potash). The crops sown at SD1 and SD2 were harvested on 29 November and 13 December 2012, respectively.

Between silking and grain-filling, furrow irrigation was applied during periods of insufficient rainfall. The first irrigation was applied on 4 October 2012 (40 mm) when the fraction of plant available soil water (PAW) in the top 0.3 m was reduced to 60–70%. The second and third irrigations were applied on 11 and 17 October 2012 (40 mm each). The SD2 treatment received an additional irrigation (60 mm) on 21 October 2012. The total amounts of irrigation applied were 120 mm in the SD1, and 180 mm in the SD2 treatments. The irrigation amounts were controlled using Parshall Flumes.

4.2.4. Crop data

The dates of key crop phenological stages were recorded when at least 50 % of the plants in a plot had attained that stage. The date of emergence was recorded when the coleoptile appeared above-ground. Tasseling was recorded when the last branch of the tassel (male inflorescence) had fully expanded at the top of the plant. The date of silking was recorded when the silk (styles connecting the stigma to the ovary in the female inflorescence) had emerged from within the husks on the primary ear (Bortiri and Hake, 2007). Silking marks the end of flowering. Physiological maturity (ripeness) was determined by the presence of “black layers” noticeable at the tip cap of the kernel attached to the cob. The presence of black layer coincides with the end of assimilate transport to the grain (Daynard and Duncan, 1969).

Cumulative thermal time (cTT in degree days, °Cd) was calculated from emergence until the occurrence of a specific phenological stage as

cTT = $\sum_{i=1}^{n} \; (T_{mean} - T_b)$

Where T_{mean} is the daily mean air temperature, T_b is the base temperature at which development ceases, and n is the number of days of temperature observations used in the summation (Ritchie and NeSmith, 1991). The T_b used in the calculations was 8°C (Jones and Kiniry, 1986).

During the season, three plants (area of 0.56 m^2) were destructively harvested (SD1: 25 August, 24 September; SD2: 8 September, 8 October), in two replications of each treatment combination to estimate above-ground biomass and leaf area. Plants were oven-dried to a constant weight for 72 hours at 70°C. The area of green leaf blades was estimated using a calibrated leaf area meter (CI-202 CID Bio-Science, Inc., Camas, WA, USA), and the data were used to estimate the leaf area index (LAI, leaf area per unit ground area).

At final harvest (29 November and 13 December 2012), the plant density, number of ears, and plant height were recorded on the harvest area of 21 m^2 (four central rows of each plot). The harvest was done by cutting whole plants at the soil surface. To estimate grain yield, the kernels were shelled from the cobs by hand. The percentage grain moisture was determined on a subsample using a seed moisture meter (Model 62615, Dickey-John Corporation, Auburn, AL), and the grain yield was subsequently adjusted to 12.5% moisture content. Samples of 10 plants were oven-dried for 72 hours at 70°C to estimate the percentage moisture at harvest. The stover yield from the harvested plot was subsequently adjusted to 0% moisture. The harvest index (HI) was calculated as the ratio of grain yield to total above-ground biomass. The yield components (number of kernels per ear, and 100-kernel weight) were assessed on five ears that were randomly selected from each plot.

4.2.5. Soil moisture measurements

The initial soil moisture contents at sowing of the SD1 and SD2 treatments were determined gravimetrically from four samples taken at 0–0.15 m, 0.15–0.30 m, 0.30–0.60

m, 0.60–0.90 m and 0.90–1.20 m soil depths covering the experimental area. For seasonal soil moisture monitoring, a calibrated neutron moisture meter (Model 503 of Campbell Pacific Nuclear Corporation, US) was used. Aluminium access tubes were installed in the plot centre in two replicates of sowing date by N treatment combinations of cultivar *Melkassa-2*. Neutron probe measurements were taken every one to two weeks throughout the cropping season at the soil depths specified above. Soil moisture in the top 0–0.15 m was measured gravimetrically for all plots.

Water productivity is defined as the ratio of agricultural outputs to the amount of water consumed (Kijne et al., 2003). Evapotranspiration (ET) from sowing to maturity was computed from rainfall, irrigation and soil moisture measured. In ET calculation, the effect of upward capillary flow, drainage and runoff were neglected. ET was calculated as

$$ET = R + I - \Delta SW$$

Where R is the in-crop rainfall (mm), I is the applied depth of irrigation (mm), ΔW is the net change in soil water storage within the rooting depth since sowing to physiological maturity

The water productivity (WP) index was calculated as

$$\text{Water productivity} = \frac{\text{Grain yield (kg ha}^{-1}\text{)}}{\text{Total seasonal ET (mm)}}$$

4.2.6. Statistical analysis

All data were analysed using analysis of variance (ANOVA) in GenStat (14th edition; VSN International, 2011) with the factors 'sowing date', 'N fertiliser rate', and 'cultivar'. Crop phenology, yield, and yield component data were analysed accounting for the split-plot design of the experiment. Three-way interactions were non-significant and are therefore not presented here. Fisher's least significant difference (LSD) test at 5% and 1% probability levels was used to determine significant differences among treatment means.

The statistical model was:

$Y_{ijkl} = \mu + B_i + SD_j + N_k + C_l + (SD \times N)_{jk} + (SD \times C)_{jl} + (N \times C)_{kl} + (SDxNxC)_{jkl} + \gamma_{ij} + \varepsilon_{ijkl}$

Where Y_{ijkl} is the dependent variable associated with the k^{th} and l^{th} factor level of the sub-plot within the j^{th} whole-plot in the i^{th} block, μ is the population mean, B_i is the component common to all sub-plots in the i^{th} block (i=3), SD_j is the main effect component of the j^{th} level of main plot treatments of sowing date (j=2), N_k is the main effect component of the k^{th} level of sub-plot treatments of N application (k=2), C_l is the main effect component of the l^{th} level of sub-plot treatments of cultivar type (l=2), $(SD \times N)_{jk}$ is the effect of the interaction between SD_j and N_k, $(SD \times C)_{jl}$ is the effect of the interaction between SD_j and C_l, $(N \times C)_{kl}$ is the effect of interaction between N_k and C_l, $(SDxNxC)_{jkl}$ is the effect of the interaction between SD_j, N_k, and C_l, γ_{ij} is the random component common to all sub-plots in the $(i,j)^{th}$ whole plot, and $\varepsilon_{ijkl}$is the random component to the sub-plots with the k^{th} and l^{th} levels of N_k and C_l respectively in the $(i,j)^{th}$ whole-plot. γ_{ij} and ε_{ijkl} are assumed to be normally and independently distributed about zero means. There are two kinds of error: σ_γ^2 represents the random effect of whole plots, and σ_ε^2 represents the random effect of split-plots.

4.3. Results

4.3.1. Seasonal conditions and crop phenology

The total seasonal rainfall (June to October) was 43% above the long-term average in 2012. However, the rainfall distribution was highly uneven; the June rainfall (22.4 mm) was 58% below average, and the July to September rainfall (796 mm) was about 90% above the long-term average (Fig. 4.1). As a consequence of the low June rainfall, sowing was delayed until 6 July 2012 (SD1), and carried out immediately after a three-day heavy rainfall event of 144 mm.

Maize emerged seven days after sowing (DAS) for both sowing dates. In the earlier sown crop (SD1), the silk emerged at 73 DAS (17 September 2012), and the thermal time required from emergence to silking was 841°Cd (Fig. 4.2). In the late sown crop (SD2), silking occurred at 72 DAS (30 September 2012), and the maize required 836°Cd from emergence to silking. The cumulative in-crop rainfall from sowing until silking was 684 mm at SD1, and 456 mm at SD2. Supplemental irrigation for both early and late sown crops commenced on 5 October 2012. In-crop rainfall plus irrigation was 804 mm for SD1 and 637 mm for SD2.

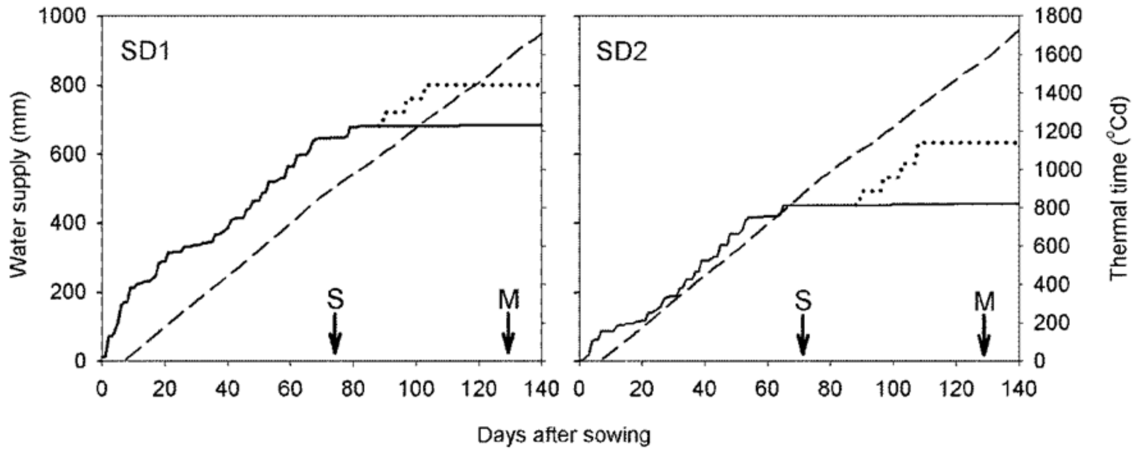


Figure 4.2: Seasonal growth conditions for maize sown at two dates (SD1: 6 July; SD2: 20 July) at Melkassa, 2012: cumulative in-crop rainfall (–), cumulative in-crop rainfall plus irrigation (•••), and cumulative thermal time (---) from emergence to silking (S), and physiological maturity (M).

Sowing date by N treatment interactions were significant for the number of days from sowing to tasseling ($p < 0.001$; LSD = 2.12) and silking ($p = 0.009$; LSD = 1.11), but not for days from sowing to physiological maturity ($p > 0.05$) (Table 4.2). Specifically, the application of N100 significantly shortened the number of days required from sowing to tasseling and silking. This reduction was three and two days for SD1, and two and zero days for SD2 (Table 4.2). Across sowing dates and N levels, the cultivar *Melkassa-3* required on average 69 days (793°Cd) from sowing to tasseling. This was one day less than cv. *Melkassa-2*, which required 70 days (805°Cd; $p = 0.01$). However, both cultivars required 73 days to reach silking (845°Cd), and 128 days for physiological maturity (1479°Cd), irrespective of sowing date and N application.

Table 4.2: Crop phenology, yield components, grain yield, biomass, and harvest index of maize (M-2: cv. *Melkassa-2*; M-3: cv. *Melkassa-3*) sown on two dates (SD1: 6 July 2012; SD2: 20 July 2012), and grown using two nitrogen fertiliser rates (N0: 0 kg N ha^{-1}; N100: 100 kg N ha^{-1}) at Melkassa, Ethiopia. One standard error of mean (+/-) is given in parentheses. The probability of F values for interactions and main effects are provided in the text.

		SD1		**SD2**	
		N0	**N100**	**N0**	**N100**
Phenology[a]					
Days to tasseling	**M-2**	73 (0.33)	71 (0.33)	70 (0.67)	68(0.33)
	M-3	71 (0.66)	67 (0.33)	69 (0.58)	67 (0)
Days to silking	**M-2**	75 (0.33)	72 (0)	72 (0.87)	72 (0.67)
	M-3	73 (0.33)	72 (0)	72 (0)	72 (0.67)
Days to maturity	**M-2**	128 (0.67)	128 (0.88)	129 (0.67)	128 (0.88)
	M-3	128 (0.58)	127 (0)	129 (0.33)	128 (0.33)
Yield components					
Ears m^{-2}	**M-2**	6.07 (0.19)	6.11 (0.51)	5.19 (0.05)	5.77 (0.25)
	M-3	6.38 (0.15)	6.22 (0.53)	5.47 (0.29)	5.95 (0.62)
Kernels ear^{-1}	**M-2**	344 (38)	433 (12)	295 (29)	337 (22)
	M-3	402 (13)	463 (12)	291 (12)	379 (28)
100-Kernel weight (g)	**M-2**	28.9 (1.55)	33.6 (0.35)	25.4 (0.64)	26.5 (1.23)
	M-3	25.4 (0.76)	26.5 (0.92)	23.2 (1.29)	25.6 (1.91)
Grain yield, total above-ground biomass					
Yield (t ha^{-1})	**M-2**	2.73 (0.45)	4.77 (0.09)	2.06 (0.19)	2.72 (0.10)
	M-3	2.99 (0.36)	5.00 (0.17)	2.66 (0.20)	3.51 (0.03)
Biomass (t ha^{-1})	**M-2**	11.20 (0.95)	17.60 (1.45)	9.61 (0.86)	13.94(1.45)
	M-3	10.16 (0.06)	17.45 (1.91)	11.69 (0.76)	15.58 (1.93)
Harvest index	**M-2**	0.24 (0.04)	0.27 (0.04)	0.21 (0.07)	0.20 (0.05)
	M-3	0.29 (0.06)	0.29 (0.07)	0.23 (0.04)	0.23 (0.04)

[a]As days from sowing to the phenological stage specified.

4.3.2. Grain yield

There were significant 2-way interactions between the effects of sowing date and N application rate ($p < 0.001$; LSD = 1.37), and sowing date and cultivar ($p = 0.034$; LSD = 1.37) on grain yield (Table 4.2). The application of N100 increased grain yield by 71% for SD1 but only by 32% for SD2. Without N application (N0), the yield was statistically the same for both sowing dates. Compared to cv. *Melkassa-2*, the grain yield of cv. *Melkassa-3* was 27% lower for SD1 and 59% lower for SD2.

4.3.3. Total biomass and leaf area index

The total above-ground biomass at 80 DAS and at final harvest (145 DAS) was the same for both sowing dates. At 125 DAS, biomass in the SD1 treatment was significantly greater than in the SD2 treatment ($p < 0.013$, LSD = 3.43; Fig. 4.3a). The application of N100 significantly increased total biomass measured at 125 DAS ($p = 0.003$, LSD = 1.84; Fig. 4.3b) and at harvest ($p < 0.001$; LSD = 1.59; Table 4.2), but not at 50 and 80 DAS.

The LAI was significantly affected by N at all growth stages (Fig. 4.3c). The application of N100 increased the LAI by 13.5 % ($p < 0.001$, LSD = 0.29), 32% ($p < 0.001$, LSD = 0.43), and 18% ($p = 0.009$, LSD = 0.43) at 50, 80 and 125 DAS, respectively. The LAI values steadily increased and reached a maximum shortly after silking.

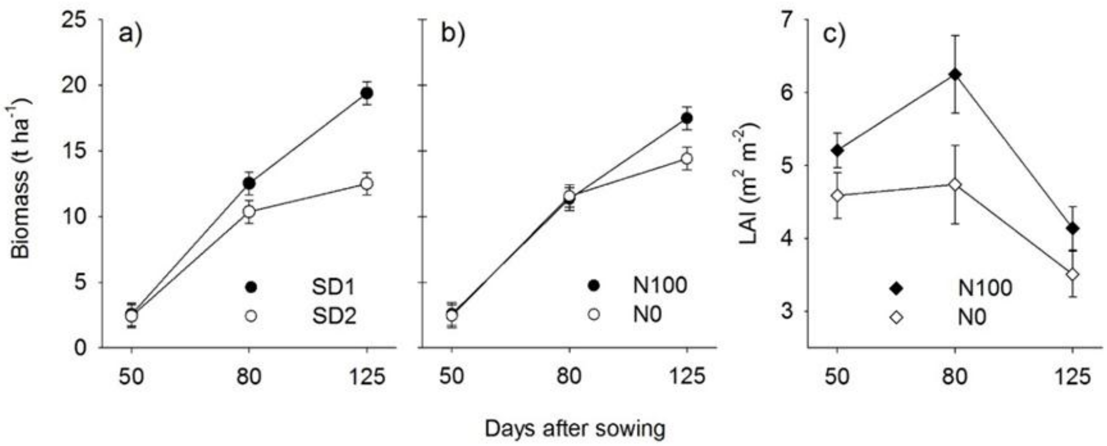


Figure 4.3: Total above-ground biomass until harvest under (a) two sowing dates (SD1: 6 July; SD2: 20 July), (b) two nitrogen fertiliser rates (N0: 0 kg N ha^{-1}; N100: 100 kg N ha^{-1}), and (c) changes in green leaf area index (LAI) with N0 and N100 for maize grown at Melkassa in 2012.

4.3.4. Yield components and harvest index

Sowing maize earlier (SD1) increased the number of ears by approximately 0.7 ears m^{-2} compared to SD2 (6.20 vs. 5.52; $p = 0.005$; LSD = 0.8) (Table 4.2). Similarly, the number of kernels ear^{-1} was 26% greater in the SD1 crop compared to SD2 (411 vs.326; $p = 0.023$; LSD = 57), and 100-kernel weight was increased by 22% in the SD1 crop (30.8 vs. 25.2 g; $p = 0.027$; LSD = 4.1). The application of N increased the number of kernels ear^{-1} by 21% (403 vs. 333; $p = 0.002$; LSD = 37.9) and 100-kernel weight by 10% (29.3 vs. 26.6 g; $p = 0.007$; LSD = 0.18). There was a significant interaction between the effects of sowing date and N application rate on HI ($p = 0.045$; LSD = 0.015) (Table 4.2). The HI was only affected by cultivar treatment. Across sowing date and N treatments, the HI of cv. *Melkassa-3* was slightly greater than that of cv. *Melkassa-2* (0.26 vs. 0.23; $p = 0.05$; LSD = 0.05).

4.3.5. Soil water

Compared to the volumetric soil water contents (SW%) measured at sowing, the SW% in 0–1.2 m soil depth at about 65 DAS was on average 40% greater in the SD1 plots and 44 % greater in the SD2 plots (Fig. 4.4). This was due to high amounts of rainfall during this period, i.e., 420 mm at SD1 and 565 mm at SD2. The SW% (at about close to the physiological maturity of the crop) was greater in the unfertilised crop (42% for SD1 and 46% for SD2) compared to when N100 was applied (36% for SD1 and 44% for SD2) suggesting that soil water extraction by maize was greater when fertiliser was applied. Over the growing season, the application of N increased the amount of SW% depleted by 29% compared to the unfertilised treatment. Most of the SW% reduction occurred in the upper 0.6 m of soil regardless of the sowing dates and the amount of N applied. Changes in SW% at 0.6–0.9 m and 0.6–1.2 m depths differed more between N treatments than between sowing date treatments. Over the entire growing season, there were only small changes in SW% at 0.6–0.9 m and 0.9–1.2 m depths for the N0 treatment however large changes in the N100 treatment were observed. Across sowing dates, the SW% in the crop fertilised with N100 declined by more than 24% from about 60 DAS onward compared to the unfertilised crop.

Regardless of N fertiliser application, crop water productivity was greater for early-sown maize (4.5 kg ha^{-1} mm^{-1}) than for the late-sown maize (4 kg ha^{-1} mm^{-1}). As application of N fertiliser was raised from N0 to N100, the crop water productivity increased by 55% (3.5 vs. 5.5 kg ha^{-1} mm^{-1}). For the late sown maize, application of N100 was inefficient however with an 8% increase in water productivity (4.2 kg ha^{-1} mm^{-1}) over N0.

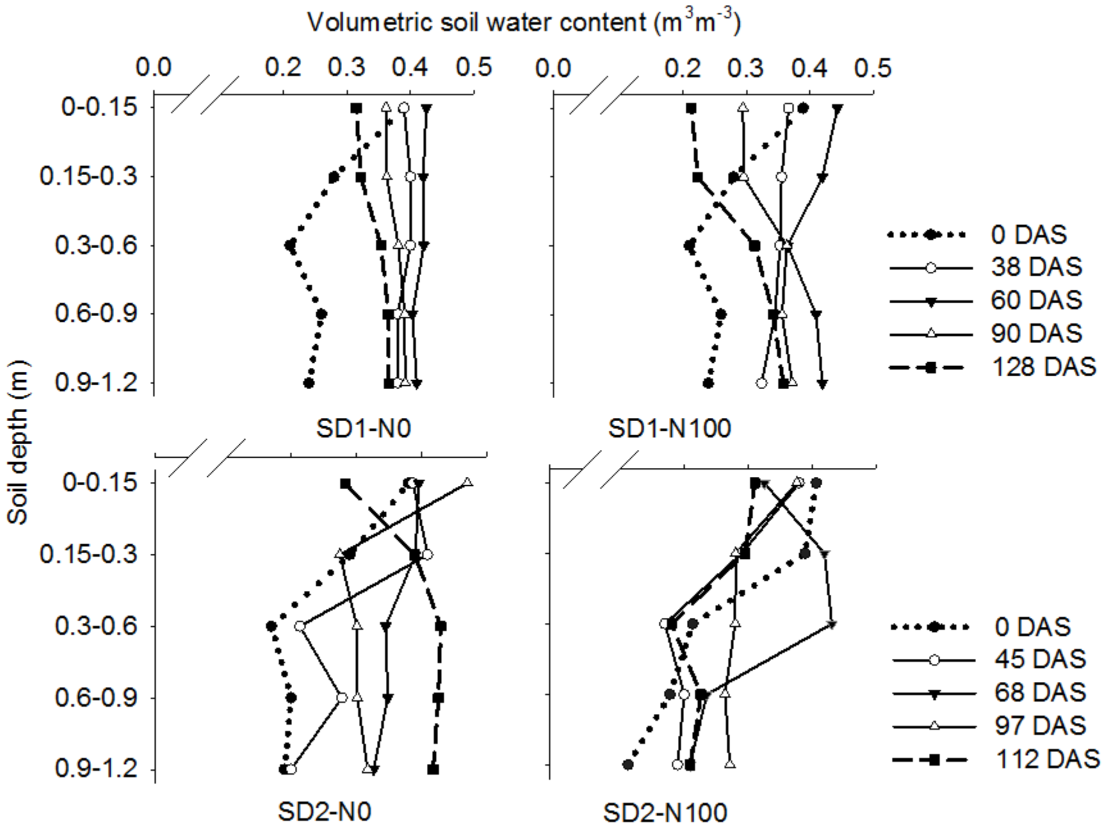


Figure 4.4: Soil water profiles at different days after sowing (DAS) in maize (cv. *Melkassa-2*) grown at Melkassa in 2012: the sowing dates were 6 July (SD1) and 20 July (SD2), and the nitrogen fertiliser rates were 0 kg N ha^{-1} (N0) and 100 kg N ha^{-1} (N100).

4.4. Discussion

This study focused on maize cultivar responses to sowing date and N fertiliser to develop a minimum data set (Hunt and Boote, 1998) for applying APSIM-Maize in the CRV region of Ethiopia. These three management options were chosen as they are typically used by smallholder farmers to deal with the uncertainty and high level of production risk associated with rainfall variability in the study region (Fujisaka et al., 1996a; Rao et al., 2011; Kassie et al., 2013a).

In contrast to rainfall, daily mean maximum and minimum temperatures rarely fluctuate by more than 2°C during the maize growing season (June–September; Fig. 4.1). This explains why the number of days and thermal units required from sowing to flowering and maturity were similar for both sowing dates. A similar response was reported by Muchow and Carberry (1989) for maize sown at three dates in a semi-arid tropical climate. Thus, differences in seasonal environment-types associated with the sowing dates SD1 and SD2 were primarily related to differences in timing and amounts of rainfall.

Late-sown maize received 42% less rainfall until silking than the earlier sown maize crop, which caused a reduction in kernel numbers, kernel weight, and ultimately grain yield (Table 4.2). Kernel numbers are determined two weeks either side of silking (Singh and Singh, 1995; Andrade et al., 2002; Boomsma and Vyn, 2008) and water stress during this critical period can reduce pollen life span and ear growth (Bänziger, 2000; Bruce et al., 2002) to substantially reduce kernel numbers and ultimately yield (NeSmith and Ritchie, 1992). The results suggest that there are differences in the sensitivity of cultivars to water stress during silking (Efeoğlu et al., 2009; Badu-Apraku et al., 2013) as the yield reduction with late sowing was significantly less in cv. *Melkassa-3* (-23%) than in *Melkassa-2* (-36%). Thus, cv. *Melkassa-3* (SADVE) might be a more drought tolerant alternative for farmers to manage rainfall variability. According to evaluation of farmers, who were engaged in participatory plant breeding experiments across semi-arid region in the CRV of Ethiopia, better drought tolerance was one of the most desirable characteristics of cv. *Melkassa-3* that make many farmers to prefer the cultivar over all other candidate germplasm (Abebe, 2005).

Previous studies reported a five day difference in physiological maturity between the cultivars *Melkassa-2* and *Melkassa-3* (Bogale et al., 2011). Under the conditions of this study, however, both cultivars required similar amounts of thermal units to reach physiological maturity after either sowing date (Table 4.2). It is difficult to explain the discrepancy between this study and that of Bogale et al. (2011) as no information on thermal time requirements for physiological maturity was provided in their results. These two cultivars are fairly similar in terms of their growth duration (maturity grouping), and both cultivars are recommended for the beginning of the main rainy season (June–September) in the CRV of Ethiopia. Farmers in the CRV often sow medium- to late-maturing maize cultivars during the short rainy season (March–May) so that they can mature during the main rainy season (June–September) (ICRA, 1999). In most developing countries however, the average number of days required for a crop to reach flowering or physiological maturity is the only indicator of the crop cycle duration. Instead, it is desirable to have crop phenology characteristics of each cultivar in growing-degree days depending on the required thermal time and sensitivity to photoperiod or vernalisation effect, to have all the cultivar-specific parameters that account for the developmental responses to these two factors (Grassini et al., 2015).

Environment by crop growth or development interactions influence crop cycle duration and yields differently (Tsimba et al., 2013). For example, the effect of cultivars differing in relative maturity to manage different seasons (short vs. long growing season) should be studied for the specific seasonal pattern varying in the timing of onset of rains (Kassie et al., 2013a and b). When sowing opportunities occur in any given season, farmers may still face risky choices because the consequences of decisions made at sowing are uncertain. Such aspects could be further explored in a risk analysis using crop simulation and modelling (Stapper and Harris, 1989; Chenu et al., 2011). Crop models as useful decision support tools, can be used for exploring the consequences of various management decision options, such as sowing time, cultivar maturity and N fertiliser application that interact with weather and soil factors. In effect, crop models can compensate for limitations associated with field experiments by allowing extrapolation of results to other environments beyond the experimental circumstances that are confined to specific locations or seasons (Chenu et al., 2011).

Under water-limited conditions, increasing the amount of N fertiliser often fails to increase grain yield (Gheysari et al., 2009). Resources are used more efficiently by plants or crops when there is a balance in their availability, as reflected by a higher degree of co-limitation (Sadras, 2004; Cossani et al., 2010). In this study, the yield response to N was large in the earlier sown crop (+70% compared to the N0 treatment) where rainfall and soil water-supply were favourable for growth, but substantially less (+30% compared to the N0 treatment) in the more water-limited, late sown crop. Such interactions between plant-available soil water and N have been explored for many crops, including maize (Liu and Zhang, 2007; Namakka et al., 2008; Gheysari et al., 2009; Moeller et al., 2009; Gonzalez-Dugo et al., 2010). In variable rainfall environments, water-limited growth conditions can occur any time during the season. Generally, the return from an investment in fertiliser is uncertain and risky due to large fluctuations in crop yields where rainfall variability is high (Dimes, 2011). This is often a deterrent for fertiliser use (Keating et al., 1991). However, the arguably large yield responses to N fertilisation shown here (Table 4.2, and as discussed above) for contrasting seasonal growth conditions also revealed a low capacity of the soil to supply N to the crop, i.e., the maize system was severely N-limited. As a consequence, significantly less leaf area was produced in the N0 treatment (Muchow and Davis, 1988; Pandey et al., 2001; Kamara et al., 2005). The N-limited growth conditions also delayed tasseling and silking by 2–3 days, which is a response that has been previously described for maize (Keating et al., 1991; Gungula et al., 2003). In many African smallholder farming systems, N is often more limiting than water due to nutrient mining under low/zero input, continuous cropping (Tittonell and Giller, 2013). The yield benefits from applying even small amounts of N fertiliser in smallholder maize systems could be further explored using crop modelling, and the risk caused by rainfall variability could be simultaneously quantified (Keating et al., 1991; Shamudzarira and Robertson, 2002; Moeller et al., 2009).

In the dry semi-arid regions, where water is the most limiting resource for improving crop production, maximisation of yield per unit of water (water productivity) is therefore an essential strategy (Kijne et al., 2003). In this study, the results showed that water productivity (WP) of maize can be improved with additions of N fertiliser by up to 55%, and this is expected in many regions of the world where yields are less than 40–50% those of adequately fertilised crops (Tanner and Sinclair, 1983). However, little was achieved in enhancing the crop WP when N fertiliser was applied to the late-sown maize. Compared to early sowing, the relatively low water availability for the time period between sowing and silking could be the possible reason for inducing yield-reducing water stress around flowering even though supply of N fertiliser and the subsequent water conditions might be good. For targeting high crop productivity and WP under rain-fed systems, N inputs need to be managed carefully to match water availability during crop growth cycle (Dimes et al., 2015). The WP of maize for the study area (3.5–5.5 kg mm^{-1} ha^{-1}) is more than the average WP value being reported in sub-Sahara Africa (SSA), which ranges from 0.4 to 1.0 kg mm^{-1} ha^{-1} (Rockström, 2003). Whereas WP of maize in the U.S. Corn Belt can reach up to 28 ±1.8 kg mm^{-1} ha^{-1} (Grassini et al., 2009). To achieve this great WP, observed changes in the root system and water extraction pattern between old and modern maize hybrids is considered to be the single most important factor responsible for the historical yield increase in the region (Campos et al., 2004). When there is a period of water limitation, the old hybrid extracted more water from shallow soil depths while the new hybrid appeared to be more effective at greater depths (Hammer et al., 2009). One way of improving WP of crops at the study area in the CRV region might be related to agronomic flexibility, which requires the provision of cultivars which are both drought-tolerant and drought-escaping that vary in their maturity-groups to suit early, mid, or late starts to the season (Anderson et al., 1996; Edmeades, 2008; Shiferaw et al., 2014).

The data presented here are a prerequisite for conducting a systems analysis with APSIM-Maize for water- and N-limited conditions that are typical for smallholder maize systems in the variable rainfall environments of the CRV of Ethiopia. APSIM has been widely applied to explore water- and N-limited production situations in different crops and environments (e.g., Shamudzarira and Robertson, 2002; Keating et al., 2003; Moeller et al., 2009; Song et al., 2010; Moeller et al., 2014), and has been shown to be suitable to explore resource management issues in smallholder farming systems of SSA (Carberry et al., 2002; Whitbread et al., 2010). However, the model needs to be parameterised and tested before it can be successfully applied in a new system and environment.

4.5. Conclusion

A minimum data set for modelling rain-fed maize systems in the CRV of Ethiopia is presented. Data availability is typically a major limitation for applying crop models in smallholder farming systems of SSA. The two sowing dates resulted in contrasting seasonal growth conditions in terms of rainfall, and the response of maize yield to increasing N was greater when the amounts of soil water were greater. Large responses of maize (e.g., yield and yield components, and leaf area) to applications of N fertiliser demonstrated that N limitations are a major constraint in the study system. However, there remains uncertainty about potential benefits and risks associated with the two evaluated management options because the experiment was conducted during one season only, and therefore, did not sample the wide range of inter- and intra-seasonal rainfall variability that is typical for the study environment. This limitation can be addressed using crop simulation models, which allow extrapolation beyond a single season or location. Subsequently, the data presented here were used to evaluate key aspects of model performance before conducting a systems analysis of sowing date and fertiliser N effects on maize productivity across a wide range of seasons in the study environment. The modelling results are presented in Chapter 5.

Chapter 5 Maize (*Zea mays* L.) productivity as influenced by sowing date and nitrogen fertiliser rate in the Central Rift Valley of Ethiopia: Parameterisation, evaluation and application of APSIM-Maize

Abstract

APSIM-Maize was used to simulate maize (*Zea mays* L.) growth and development, and changes in the soil resource at Melkassa, in the Central Rift Valley of Ethiopia. The model simulated the soil water dynamics (0–1.2 m depth) reasonably well for cv. *Melkassa-2* sown at two dates and grown at two rates of fertiliser N (0 and 100 kg N ha^{-1}) as indicated by a Root Mean Squared Error (RMSE) of 0.017–0.074 mm mm^{-1}, relative RMSE (n-RMSE) of 9.5–24%, and an r^2 of 0.77–0.94. An assessment of model performance against six independent data sets showed that APSIM-Maize was able to simulate the dates of silking (RMSE = 1 d; n-RMSE = 2.7%; r^2 = 0.80) and physiological maturity (RMSE = 1.50 d; n-RMSE = 1.6%; r^2 = 0.89), grain yield (RMSE = 0.39 t ha^{-1}; n-RMSE = 11%; r^2 = 0.68) and biomass production (RMSE=0.48 t ha^{-1}; n-RMSE=10.2%; r^2=0.66) for June-sown maize (2006–08, 2010–12) grown at different rates of N supply (43 to 100 kg N ha^{-1}). This study proved the ability of the APSIM model to represent realistically complex interactions between crop, soil, weather and management. Subsequent scenario analyses (1990–2014) showed large shifts in cumulative distribution functions towards greater yields with the application of 50 kg N ha^{-1} compared to unfertilised maize irrespective of the sowing window (i.e., May, June and July). Assuming that a farmer would attempt to obtain at least 2.5 t ha^{-1} of maize yield in any given year, the simulations showed that this was only achievable with additions of N fertiliser. The maximum chance of exceeding 2.5 t ha^{-1} was 50% for May sowing at N rates of 50 kg N ha^{-1} and 100 kg N ha^{-1}, 64% for June sowing with 50 kg N ha^{-1}, and 72% for July sowing with 100 kg N ha^{-1}. A well-tested crop simulation model can assist in exploring the production risks and yield uncertainties associated with rainfall variability in the dryland environments of Ethiopia.

5.1. Introduction

Variability in rainfall is a principal source of fluctuations in food production, particularly in the semi-arid tropical countries such as Ethiopia (Conway and Schipper, 2011; Demeke et al., 2011; Kassie et al., 2014). Systematic analyses of crop responses to management practices are of particular use to rain-fed farming systems in the semi-arid area where there is high uncertainty in crop production. As farming systems are highly variable in seasonal rainfall and soil type, applying the conventional field experiments can provide useful information on crop and soil responses as affected by limited combinations of climate, soil, and management situations (Bationo et al., 2012). With field experiments, however, they are unlikely to cover the full range of possible climate, soil, and management factors to sufficiently understand the effect of climatic risks and their interaction with crop management decisions in crop production systems. As long-term field experiments at several locations would be extremely costly, if not physically impossible (Muchow et al., 1991), inference from a specific field experiment can be misleading if it is applied beyond the limited extrapolation domain; it is often ineffective to recommend agronomic interventions for the wide scale of a given environment (Simane et al., 1994; Matthews et al., 2002; Dixit et al., 2011; Bationo et al., 2012). Instead, crop models with long-term-term sequences of climatic data can play an important role in adding value to any field experiment by effectively extrapolating the experimental results by making the necessary adjustments to suit the new environmental conditions (Dimes et al. 2003; Saseendran et al., 2008; Boote et al., 2013). As a result, crop models can be used to study the challenge of complex farming systems having variable climate and diverse soil types in which *a priori* risk can be quantified through examining probabilistic estimates of yield (Meinke et al., 2001; Matthews et al., 2002; Hansen, 2005), which in turn enable us to effectively determine the scale of crop responses for a range of possible combinations of agronomic management and genetics factors (Whitbread et al., 2010; Rezaei et al., 2015).

Nevertheless assessment of production level and risk associated with management options can be provided using crop models at a much lower cost and in a more rapid manner (Cooper et al., 2008; Carberry et al., 2009; Hochman et al., 2009). Site-specific data on weather, soils, and the cropping system are required for parameterising as well as for rigorously evaluating the models well enough under a variety of environment and management practices before researchers can be confident in using such models as research or decision tools (Van Ittersum et al., 2003; Gaydon et al., 2017). This helps ensure models are robust in accurately simulating what might happen when agronomic practices are changed for a range of climates and soils before they are reliably applied in identifying effective management alternatives that are suitable to a specific farmers' goal and capability in the face of climate variability and uncertainty (Nix, 1984; Hansen, 2005; Dixit et al., 2011; Dimes, 2011; Stern and Cooper, 2011).

The Agricultural Production Systems sIMulator (APSIM) has been widely tested and applied successfully in contrasting production situations and a range of dryland environments (Moeller et al., 2009, 2014; Akponikpè et al., 2010; Fosu-Mensah et al., 2012; Kamanga et al., 2014). The MAIZE module within APSIM is a derivate of CERES-Maize (Jones and Kiniry, 1986). Earlier versions of CERES were applied to simulate water and N constraints on maize (*Zea mays* L.) yields in Kenya and Australia (e.g., Carberry and Abrecht, 1991; Keating et al., 1991). Testing the model under a range of water and N stress revealed the need of model enhancement to accurately simulate the effects of water and N deficits on crop phenology, canopy development, grain set and plant mortality (Carberry and Abrecht, 1991). The important changes made in APSIM-Maize included the sensitivity of phenology to water and N stress, and responsiveness of grain number to better reflect yield responses at a range of plant population densities (Keating et al., 2003). These changes helped to improve the predictive performance of the model in terms of maize development, and assimilate accumulation in water- and N-limited production situations (Thornton et al., 1995; Shamudzarira and Robertson, 2002; Song et al., 2010). Apart from this, several other model modifications enable APSIM to simulate the typical features of smallholder farming systems which practice low levels of external input for crop production (Shamudzarira et al., 2000; Probert, 2004). In several parts of Africa, APSIM has been widely evaluated under smallholder farming systems to quantify seasonal variability in crop yields due to management changes, and to identify the potential for resource-limited farmers under different climate conditions (Keating et al., 2000; Shamudzarira et al., 2000). However, extensive and high quality data on environment, cultivar and crop management is required for deriving the specific cultivar- and soil-related parameters that are the essential inputs for the model, as well as for evaluating if the model is realistic in simulating the key soil and crop processes in response to varying management and environmental conditions (Bationo et al., 2012; Hoogenboom et al., 20012; Boote et al., 2015).

Like many Sub-Saharan Africa countries, data suitable for model parameterisation and evaluation in Ethiopia are scarce and often unavailable (Bontkes and Wopereis, 2003; Kassie et al., 2014). This is a serious constraint for the application of crop models (Whitbread et al., 2010; Dixit et al., 2011; MacCarthy et al., 2015) since they are site specific in nature and should not be adapted to new environments until the crop models are locally parameterised and evaluated using empirical data that are generated from the established field experiments (Jones et al., 2001; Van Ittersum et al., 2003). Once the key model parameters are carefully measured or estimated by fitting the overall model to observed data (Wallach et al., 2014), crop models with the derived parameter values need to be critically judged if they are robust and realistically simulate the various crop attributes and key soil processes when they are compared against independent data from various treatments/experiments which was not used in the model parameterisation. The performance of the model can then be evaluated by testing whether the strength of the relationship between the locally measured data values and the model simulated results is good enough (Jamieson et al., 1991; Hunt and Boote, 1998; Timsina and Humphreys, 2006) to establish credibility and provide confidence in the utility of APSIM for modelling the maize system in response to various tactical and strategic management decisions on real farms. To address this, a field experiment was conducted at Melkassa in the Central Rift Valley (CRV) of Ethiopia (Chapter 4). For effective application of the APSIM model, the experiment was designed to obtain a comprehensive and good quality dataset in which numerous variables were measured containing both in-season and end-season data related to key crop growth, development and yield, as well as dynamics of soil water and nitrogen (N) throughout the growing season.

The overall aim of the study was therefore to generate experimental data on phenology, leaf area index (LAI) and biomass dynamics, along with yield and yield components of maize that can be used to parametrise and evaluate the APSIM model for the local conditions in the CRV of Ethiopia. More specifically, the objectives of this study were to: (i) produce essential input-parameter sets for improving the capabilities of APSIM in modelling both crop and soil processes in the Melkasa area, as representative of the CRV of Ethiopia;(ii) evaluate the capacity of the parameterised APSIM-Maize against independent data for accurately simulating crop phenology, grain yield and biomass production before the model can be reliably applied to modelling the maize system in the region, and (iii) subsequently apply APSIM-Maize with long-term-sequences of climatic data in running various management scenarios to explore probabilistic estimates of grain yield under varying sowing dates and rates of N fertiliser application under the local weather and soil conditions in the region.

5.2. Materials and Methods

5.2.1. Model description

APSIM is an agricultural production system simulator developed and used for improving risk management under variable climate (Keating et al., 2003; Holzworth et al., 2014). A configuration of APSIM model (version 7.5) was used on a daily time step, which included the Maize crop module (*APSIM-Maize*), and the APSIM soil water module (*SoilWater*), soil Nitrogen module (SOILN) and SurfaceOrganic Matter module (*SurfaceOM*). A description of all the APSIM modules can be found at www. apsim.info (including references and source code). A brief overview of the modules is provided herein.

APSIM-Maize

The MAIZE module simulates maize development, growth, yield, and N accumulation on a daily-time step in response to daily weather (temperature, rainfall and solar radiation), soil water, soil N, and crop and soil management. Phenology is simulated using a photo-thermal-time approach (Jones and Kiniry, 1986), which assumes that the development rate increases as a multi-linear function of thermal time for the 0 to 44°C temperature range with an optimal temperature for development of 34°C. The phenology routine calculates 11 growth stages and nine phases (time between stages). Each day, the phenology routine calculates the accumulated thermal time accumulation (in degree days; °Cd) from eight 3-hour estimates, third-order polynomial interpolations between the minimum and maximum daily temperatures (Kumudini et al., 2014), except the duration between sowing and germination, which is influenced only by plant available soil moisture. Accumulated thermal time is used to determine the duration of each phase. Between emergence and silking, daily thermal time accumulation is reduced by water and/or N stresses to result in delayed phenology when the plant is under stress. Maize is assumed to be insensitive to photoperiod until the end of the juvenile stage. Between the end of the juvenile phase and floral initiation, the development rate can be sensitive to photoperiod depending on the cultivar. This is followed by an inductive phase (photoperiod sensitive), which is terminated by tassel initiation. Because maize is a short-day plant, tassel initiation is delayed if day length exceeds 12.5 hours (Jones and Kiniry, 1986).

Biomass accumulation is simulated as the minimum daily growth limited by either radiation (potential growth) or by crop water supply (water-limited growth). The calculation of the balance between demand for and supply of soil water is used to determine whether the environment is energy-limited (defined by radiation intercepted and radiation use efficiency) or water-limited (defined by transpiration and transpiration efficiency adjusted for vapour pressure deficit) (Monteith, 1986). The partitioning of dry matter to different plant organs depends on the growth stage. From emergence to silking, dry matter is allocated to leaves and the stem. From silking to physiological maturity, the growing grain is the largest sink for dry matter. Dry matter allocation in the grain is calculated as the product of grain number and maximum grain growth. The grain number per plant is determined by the average daily growth rate per plant between floral initiation and the start of grain filling, while grain size is determined by the grain growth rate, the effective grain-filling period, and the redistribution of assimilates post-anthesis. Crop N demand is driven by growth-stage dependent critical N concentration limits for different organs, which the simulated crop attempts to maintain. **N is** re-translocated to the grain from other plant parts and demand is driven by the critical N content but this demand is lowered if the plant is under N stress. Soil N supply is via mass flow and if crop N demand cannot be satisfied by mass flow to the roots, it is supplied by diffusive flow.

SoilWater

The soil water dynamics are simulated in the *SoilWater* module, which uses a multi-layer, cascading water balance (Jones and Kiniry, 1986). Processes include runoff, evaporation, and both saturated and unsaturated flow between conceptual soil layers. Inputs to SOILWAT include bulk density, drained upper limit (DUL), crop lower limit (CLL), and saturated (SAT) soil water contents. Saturated flow occurs as a fraction of the amount of water greater than DUL. The fraction that drains in one day is specified by the coefficient SWCON, which takes into account soil texture differences (Jones and Kiniry, 1986; Ritchie et al., 1986). SWCON values of less than 0.5 d^{-1} are typical for heavy, poorly draining clay soils, and values greater than 0.8 d^{-1} are typical for coarsely textured soils that have high water conductivity (Probert et al., 1998). When the soil water content drops below the DUL, water movement depends on the gradients between adjacent soil layers and diffusivity, which is a function of the average water content between the two layers and the diffusivity coefficients (*diffus_const* and *diffuse_slope*). The bare soil run off curve (cn2_bare) specifies the proportion of rainfall that infiltrates and the proportion that is lost through surface runoff. Runoff from rainfall is computed using the USDA curve number approach (USDA, 1972). Potential evapotranspiration (Priestley and Taylor, 1972) is calculated using an equilibrium evaporation concept. Soil evaporation is calculated via two parameters U and CONA, which determine the first and second stages of soil evaporation (Ritchie, 1972). For the first stage, the soil is sufficiently wet and the soil evaporation is energy-limited and occurs at a rate equal to the potential evaporation rate. The second stage starts when the cumulative soil evaporation exceeds the upper limit of the first stage, where the soil starts to dry and water from within the soil starts to evaporate. Crop specific parameters (crop-soil factors) determine the rate of root extension (parameter XF, 0–1 multiplier on the rate of root growth) and the maximum rate at which a crop can extract water from a particular soil layer (KL, day^{-1}). The user can specify XF for each soil layer (0: no root growth; 1: root growth at potential) to simulate barriers that can impede root growth through a particular layer (e.g., low pH and soil compaction).

SoilN and surfaceOM

The *SoilN* module describes the dynamics of carbon (C) and N for a layered soil profile. These layers are defined by the model user, and are typically the same as for the soil water simulations. Processes include soil organic matter decomposition, N immobilisation and mineralisation, and nitrification and denitrification. The input parameters for *SoilN* include pH, organic carbon (OC), *finert* (inert C fraction) and *fbiom* (microbial biomass fraction). *SoilN* treats soil organic matter as three pools, a fast decomposing microbial biomass (BIOM), intermediate (HUM), and a recalcitrant pool (INERT). The fresh organic matter (FOM) consists of the roots from the previous crop and any crop residue. The *surfaceOM* module describes the fate of surface residues and considers the above-ground crop residues that can be removed from the system, incorporated into the soil by tillage, and/or left on the surface. Residues incorporated into the soil and decomposing roots first enter the FOM pool, where they are transformed into either the rapid turnover microbial biomass (BIOM) pool or the slower turnover, less available *humic* (HUM) pool.

5.2.2. Field experiments for model parameterisation and testing

Data for model parametrisation as well as independent testing were obtained from different maize experiments conducted between 2006 and 2012 at the Melkassa Agricultural Research Center in the semi-arid CRV of Ethiopia (8º24' N, 39º12' E, 1550 m elevation). The daily weather data were used in the simulations, and included minimum and maximum temperatures, and rainfall. These variables were recorded at a meteorological station located near the experimental sites. Daily solar radiation data for the location was downloaded from the National Aeronautics and Space Administration for Climatology Resource for Agroclimatology (NASA POWER) database using the location's coordinates and elevation (Stackhouse, 2010, http://power.larc.nasa.gov/).

5.2.3. Model parameterisation

Crop, soil, weather, and management data from the 2012 field experiment (Chapter 4) were used to parameterise and subsequently run APSIM-maize. The simulated irrigation-use efficiency was 95% for all flush irrigation events (Table 5.1). Model outputs included the silking and maturity dates, the soil water dynamics, LAI, grain yield, and biomass production, and were compared with observed data. The model parameterisation is described herein.

Table 5.1: Experimental conditions for maize sown at two dates (SD1, SD2), and grown at two rates of fertiliser nitrogen (N0, N100), at Melkassa in 2012: N fertiliser rate, in-crop rainfall, amounts of supplemental irrigation, and dates of application.

Treatment	Sowing date	N (kg ha^{-1})	Date of N application	Rain (mm)	Irrigation (mm)	Date of irrigation
SD1-N0	6 July	0		684	40	4 Oct.
SD1-N100		50	5 Jul.		40	11 Oct.
		50	2 Aug.		40	17 Oct.
SD2-N0	20 July	0		456	40	4 Oct.
SD2-N100		50	20 Jul.		40	11 Oct.
		50	16 Aug.		40	17 Oct.
					60	21 Oct.

Crop parameters

In APSIM-Maize, seven cultivar-specific parameters are defined to simulate crop phenology and kernel growth (Table 5.2). Accurate estimates of these parameter values are critical for simulations of phenology, yield and yield components to be realistic. The parameters for phenological development, growth and yield formation were specified based on measured or estimated data. As the cultivar *Melkassa-2* is insensitive to photoperiod, the thermal time value for the respective process was assumed zero, and turned off in the simulations. The maximum kernel number measured in 2012 was used, and the potential kernel growth rate was set at 8 mg grain^{-1}day^{-1} as reported for a tropical maize cultivar from Ghana (Fosu-Mensah et al., 2012). The mean estimated cultivar parameters for APSIM-Maize were determined from the experimental data of SD1-N100 treatment (Table 5.1) in which the maize was grown under non-limiting N and water supply conditions (Hunt and Boote, 1998; Boote et al., 2003; Jones et al., 2003). As a result, the derived values for the specific cultivar parameter sets in APSIM-Maize resulted in appreciable agreement between the simulated and measured values for the phenological durations from sowing to flowering and sowing to maturity as well as for grain yield.

Table 5.2: Cultivar parameters fitted for APSIM-Maize to simulate the phenological development and kernel growth of cv. *Melkassa-2.*

Parameters	Values
Thermal time from emergence to end of juvenile stage (ºCd)	230
Thermal time from end of juvenile stage to floral initiation (ºCd)	0
Thermal time from flag leaf to silking (ºCd)	10
Thermal time from silking to start of effective grain-filling (ºCd)	160
Thermal time from silking to physiological maturity (ºCd)	730
Maximum kernel number per ear	440
Grain growth rate (mg grain^{-1}day^{-1})	8

Soil parameters

Input parameters for SOILWAT and SOILN are specified in Figure 5.1. The required APSIM estimates of LL and DUL were determined from soil water measurements taken at the site (Dalgliesh and Foale, 2005). The air-dry (AD) soil water content was set at 50% of CLL in the 0–0.15 m depth, 90% of CLL in the 0.15–0.30 m depth, and equal to CLL for the rest of the soil profile (Archontoulis et al., 2014). The difference between DUL and LL within the root zone was defined as extractable water-holding capacity of the soil (1.20 m soil depth). The SAT was calculated from bulk density as described by Dalgliesh and Foale (2005). The SWCON value was 0.5 d^{-1} for all soil layers. The root water extraction coefficient (KL) was 0.08 in the topsoil and decreased to 0.03 at 1.20 m soil depth (Dardanelli et al., 1997; Hammer et al., 2009). The root exploration factor (XF) was 1 for all soil layers. Initial soil water contents, amounts of NO_3-N and organic carbon were available from measurements taken prior to the establishment of the experiment at soil depths as specified as below (Fig. 5.2). The soil pH ranged from 7.8–7.9 across the soil profile.

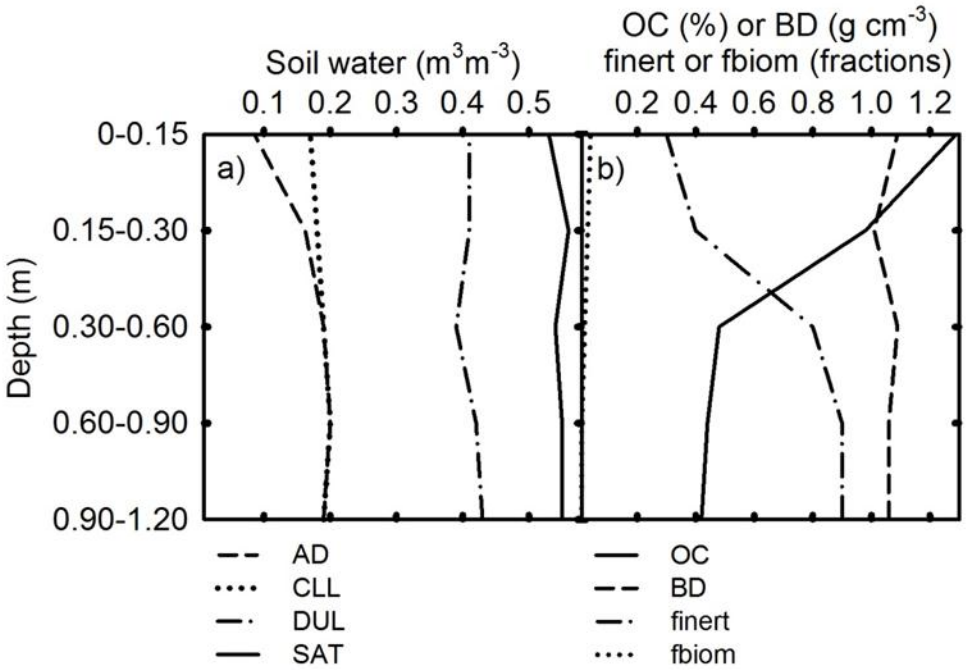


Figure 5.1: Soil characteristics at Melkassa: (a) lower (CLL) and upper limit (DUL) of plant extractable soil water, saturated (SAT) and air-dry (AD) soil water content; (b) percentage organic carbon (OC%) and bulk density (BD), fractions of inert (*finert*), and microbial (*fbiom*) carbon.

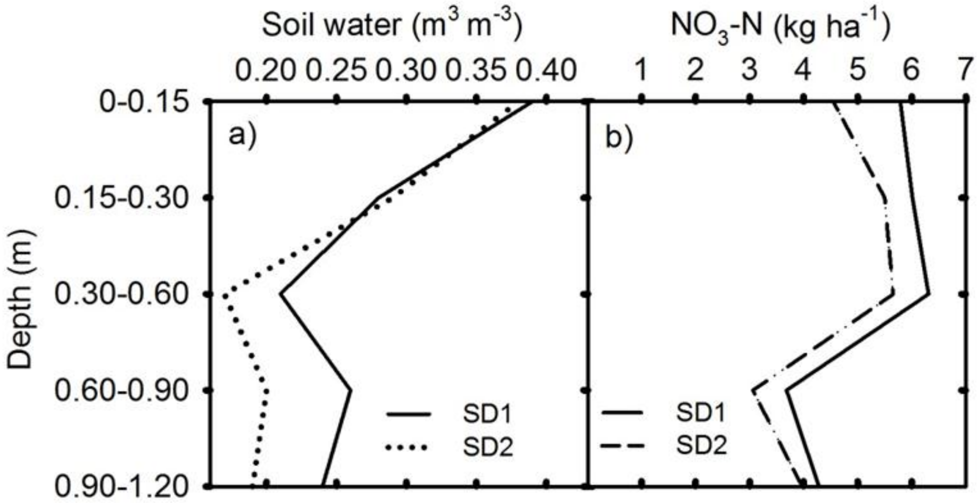


Figure 5.2: Initial soil conditions: (a) volumetric soil water and (b) NO_3-N for the maize sown on 6 July (SD1) and 20 July (SD2) 2012.

5.2.4. Independent data sets for model evaluation

Following parameterisation, the model was evaluated against six independent data sets from experiments conducted at Melkassa between 2006 and 2012 (Table 5.3). In six years, the growing season rainfall (June to September) was above average or close to the long-term average seasonal rainfall of 555 mm. The experiments assessed crop phenology, yield, and biomass of cv. *Melkassa-2* sown at different dates (between June and July) and different N application rates (Table 5.3). Standard agronomic practices were followed to keep the plots free from pests, diseases and weeds.

Table 5.3: Experiments and the respective management used for evaluating the performance of APSIM-Maize.

Year	Sowing date	Nitrogen fertiliser rate (kg ha^{-1})	In-crop rainfall (mm)
Variety evaluation experiment [a] (Melkassa Research Center, 2009)			
2006	25 June	100	595
2007	19 June	100	638
2008	24 June	64	730
Tillage and cropping system experiment [b] (Merga and Kim, 2014)			
2010	15 June	43	662
2011	25 June	43	634
2012	20 June	43	736

[a]Only*Melkassa-2* was used for modelling.

[b]Only the conventional tillage treatment was used for modelling.

5.2.5. Measures of model performance

Statistical measures for evaluating model performance were applied on simulated and observed soil water dynamics in 2012, and the six independent datasets. Other 2012 data were not included because of limited numbers of observations. To identify the true deviation of model-simulated from field-measured data, zero-origin (1:1) graphs were plotted (Mitchell, 1997). The scatterplots (1:1) produced were used to observe the pattern of differences between simulated and measured values across all datasets. The RMSE was calculated as a measure of the average absolute deviation of simulated from observed values. Model accuracy was further assessed using the relative RMSE (n-RMSE calculated as RMSE as a percentage of the observed average); and the coefficient of determination (r^2) of the best fit linear regression between observed and modelled values. Model performance was considered excellent when n-RMSE < 10%; good if 10% ≤ n-RMSE < 20%; fair if 20% ≤ n-RMSE < 30%; and poor if n-RMSE ≥ 30% (Jamieson et al., 1991; Soler et al., 2007; Archontoulis et al., 2014). The performance of the APSIM model was also evaluated between the estimate of yields provided by the farmers from their historical observations for the bad, average and good yields at Adamitulu and Melkassa, versus the simulated yield at 10%, 50% and 90% of probability, respectively.

5.2.6. Simulation scenarios

Maize yields were simulated for each year in the historical weather record (1990–2014) available at Melkassa. In the simulations, the plant density was set to 6.7 plants m^{-2}, and the sowing depth and row spacing were 0.06 m and 0.75 m, respectively. Three sowing windows (1–31 May; 1–30 June; and 1–31 July) were specified in which the timing of sowing of cv. *Melkassa-2* depended on the amount of plant-available soil water in the upper soil layer. Sowing was simulated to occur when the soil water content in 0–0.15 m depth exceeded 80% of the plant available water-holding capacity of that soil layer. If a sowing opportunity did not occur prior to the end of the sowing window, sowing was simulated on the last day of the respective window. Three N fertiliser treatments (urea-N) were simulated: N0, N50 and N100. The N0 treatment represents a management that is often chosen by resource-poor farmers. The N50 treatment represents the recommendation of government extension services for the region. The N100 treatment is an alternative management that is uncommon in the study region. A maximum of N50 was applied at sowing. For the N100 treatment, a second rate of N50 was applied 30 days after sowing. Thus, there were 25 growing seasons and maize yields for evaluation in nine simulation scenarios.

The soil type shown in Figure 5.1 was used in the simulations. Initialising soil data (soil water and soil mineral N) were as measured at the start of the 2012 experimental season for the first sowing date treatment (Fig. 5.2). In every year on the first day of the respective sowing window, initial mineral N, organic carbon and plant available soil water were reset to the starting conditions (Fig. 5.2). It is common practice among households in the study area to remove crop residue after harvesting, and store it as dry season feed for their livestock, and whatever remains on the field is often being grazed by roaming cattle (Zeleke et al., 2004; Biazin et al., 2011). It is therefore only the small amount of leftover crop residue was assumed to be retained at sowing during every season. Therefore, the amount of maize surface residue (C: N ratio = 80) was similarly initialised at 0.5 t ha^{-1} at the start of each sowing window.

5.3. Results

5.3.1. Model evaluation

Phenology

The cultivar parameters for cv. *Melkassa-2* were derived using the silking and maturity dates observed in the N100 treatment in 2012 (Table 5.2). When subsequently tested against phenology data from independent data sets (Table 5.3), the model was able to simulate the durations from sowing to silking and from sowing to physiological maturity under various conditions at Melkassa to a good degree. The RMSE, n-RMSE, and r^2 for days from sowing to silking were 1 day, 2.7%, and 0.80, and the respective values for days to physiological maturity were 1.5 days, 1.6%, and 0.89.

Soil water dynamics in 2012

The model generally simulated the soil water dynamics observed in 2012 well, though the goodness of fit was overall better for early-sown than late-sown maize (Fig. 5.3 and 5.4; Table 5. 4). For SD1, simulations of soil water contents in different soil layers showed good to fairly good agreement with the field measurements (Fig. 5.3), where the soil water contents remained close to DUL for most of the growing season. Large reductions in soil water due to lack of rainfall/irrigation in the upper soil layers (0–0.15 m and 0.15–0.30 m) were well simulated, and the model simulated all peaks in recharge associated with rainfall and irrigation.

For SD2, there was a relatively good agreement between observed and simulated soil water contents for 0–0.15 m and 0.15–0.30 m depths, while the soil water dynamics were less well simulated for deeper soil layers (Fig. 5.4). In the upper soil layers (0–0.15 m, 0.15–0.30 m), the soil water contents remained around DUL for much of the season. The observed soil water dynamics were realistically simulated for the upper soil layers. In contrast, the model over-estimated the soil water for the 0.30–0.60, 0.60–0.90, and 0.90–1.20 m soil layers, which was more obvious in the unfertilised treatment.

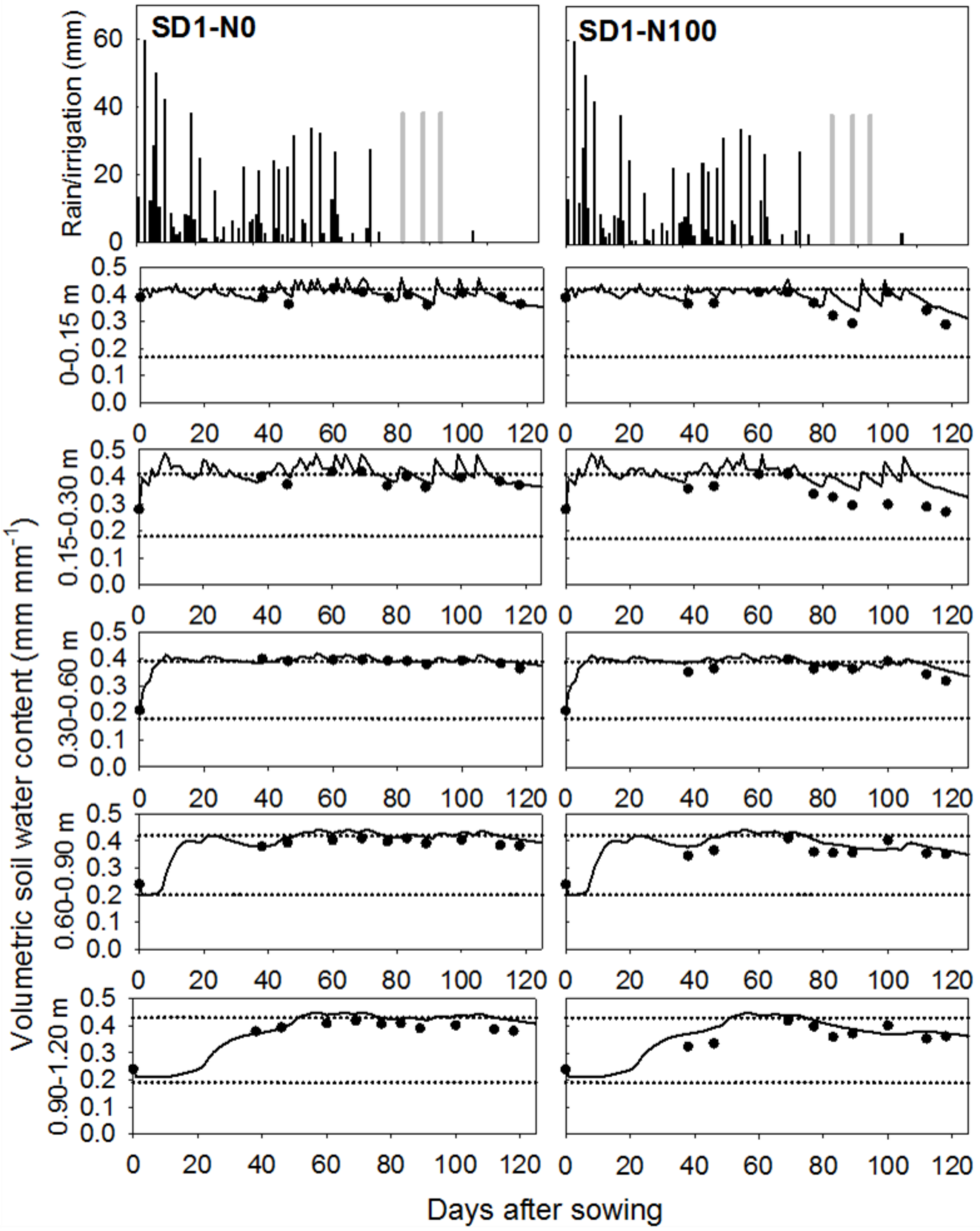


Figure 5.3: Rainfall (black bars) and irrigation (grey bars) for maize sown on 6 July 2012 (SD1) and grown at nitrogen fertiliser rates of 0 kg N ha^{-1} (N0) and 100 kg N ha^{-1} (N100), and simulated (lines) and observed (symbols) soil water contents in five soil layers (0–1.20 m depths), Melkassa, Ethiopia. The upper and lower limits of plant available soil water are indicated by the horizontal dotted lines.

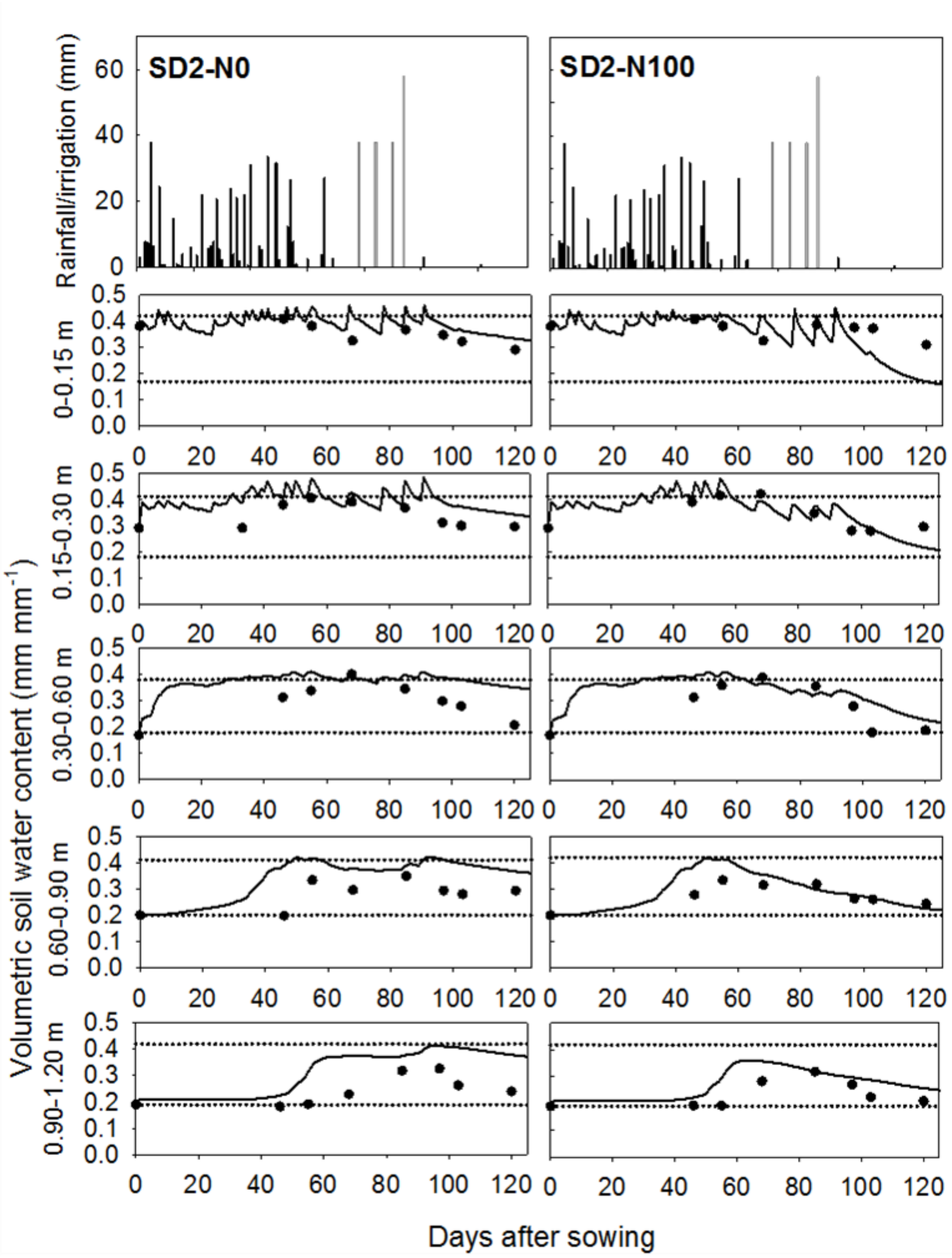


Figure 5.4: Rainfall (black bars) and irrigation (grey bars) for maize sown on 20 July 2012 (SD2) and grown at nitrogen fertiliser rates of 0 kg N ha^{-1} (N0) and 100 kg N ha^{-1} (N100), and simulated (lines) and observed (symbols) soil water contents in five soil layers (0–1.20 m depths), Melkassa, Ethiopia. The upper and lower limits of plant available soil water are indicated by the horizontal dotted lines.

Table 5.4: Statistical criteria for the goodness of fit between measured and simulated soil water contents in 0–1.2 m soil depth at Melkassa, 2012.

Treatment[a]	RMSE[b] (mm mm^{-1})	n-RMSE[c] (%)	r^2	Number of observations
SD1-N0	0.017	4.6	0.94	12
SD1-N100	0.033	9.5	0.86	12
SD2-N0	0.074	24	0.77	9
SD2-N100	0.032	11	0.87	9

[a] Sowing dates: 6 July (SD1), 20 July (SD2); Fertiliser nitrogen: 0 kg N ha^{-1} (N0), 100 kg N ha^{-1} (N100)

[b]RMSE; root mean square error.

[c]n-RMSE; RMSE as percentage of mean.

Crop performance

The simulated outputs were compared to observations in temporal biomass accumulation, final grain yield and temporal LAI. For the 2012 experiment, grain yields were accurately simulated for unfertilised maize at both sowing dates. Yields were overestimated for the N100 treatments by 11% at SD1 and by 37% at SD2. Simulated total above-ground biomass was 12–27% lower than observed except for the late-sown maize fertilised with N100 where the biomass was accurately simulated (Fig. 5.5). The temporal changes in LAI indicated that both simulated and observed values corresponded reasonably well for all treatment combinations. The LAI values increased steadily and approached a peak between 60 and 70 DAS, which was just before silking. This was well reproduced by the model. The model realistically simulated the stover-N concentration for most treatments, expect for SD2 and N100 where stover-N was over-estimated by 8.9%. The grain N concentrations were over-estimated by 6.5–22% (Table 5.5).

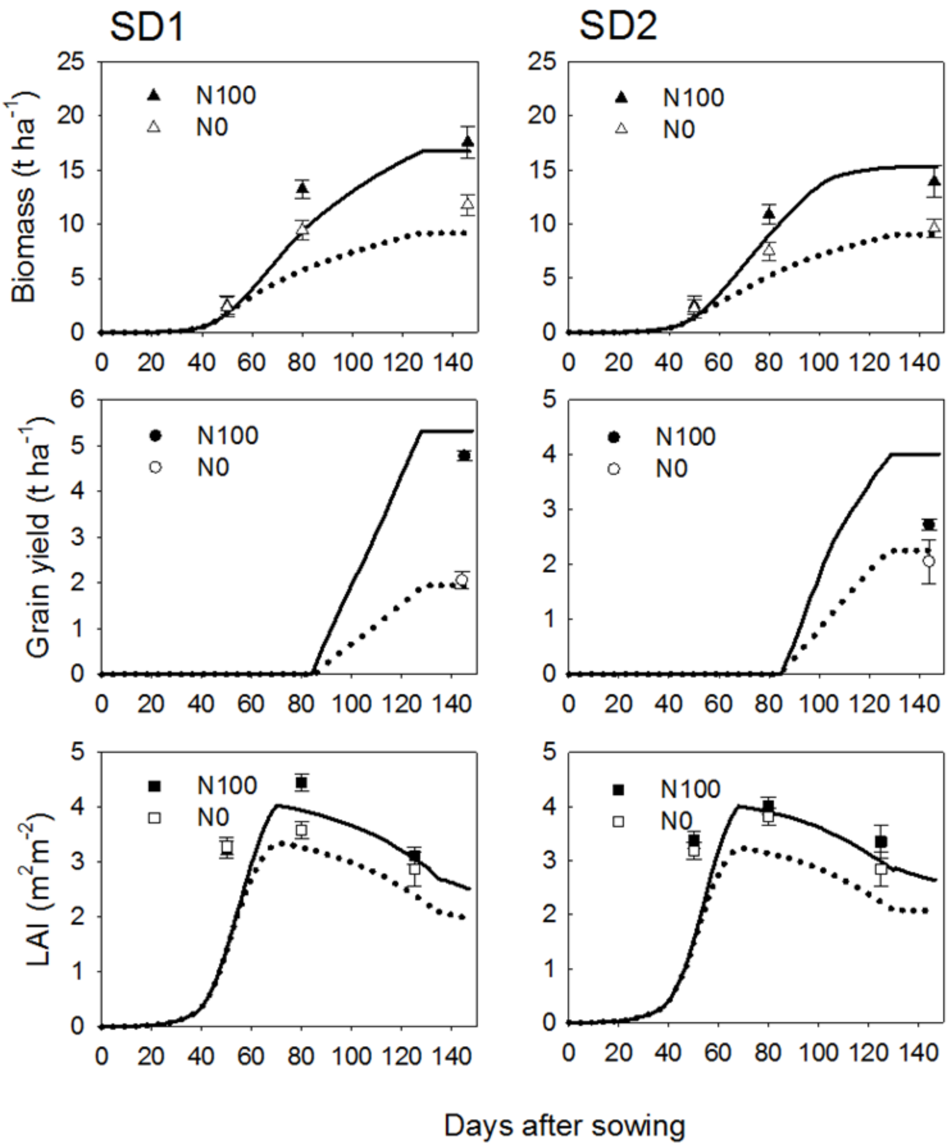


Figure 5.5: Comparison of simulated (lines) and observed (symbols) total above-ground biomass, grain yield, and LAI of maize sown on 6 July 2012 (SD1) and 20 July 2012 (SD2) and grown at two rates of fertiliser nitrogen (N0: kg N ha^{-1}; N100: 100 kg N ha^{-1}) at Melkassa, Ethiopia. Vertical bars represent the standard error of means.

Table 5.5: Measured and simulated stover and grain N concentrations of maize sown on 6 July (SD1) and 20 July (SD2), and grown at fertiliser rates of 0 kg N ha^{-1}(N0) and 100 kg N ha^{-1} (N100) at Melkassa, 2012. Values in parentheses represent the standard error of mean.

Treatment	Stover N (%)		Grain N (%)	
	Measured	Simulated	Measured	Simulated
SD1-N0	3.46 (0.06)	3.78	2.58 (0.12)	2.75
SD1-N100	6.19 (0.13)	6.59	6.34 (0.09)	8.26
SD2-N0	3.22 (0.13)	3.40	2.23 (0.10)	3.19
SD2-N100	8.22 (0.17)	9.42	4.45 (0.30)	5.45

To prove model accuracy, the model was tested against independent datasets other than the one used for model parameterisation. Therefore, APSIM-Maize with the derived parameters was subsequently evaluated against independent datasets from six experiments at Melkassa, Ethiopia (Fig. 5.6). According to assessment of the model, it was found that APSIM-Maize simulated phenological development of cv. *Melkassa-2* reasonably well, with RMSE, n-RMSE and r^2 values of <2 days, <3% and $\geq$0.80–0.89, respectively. The simulated values for grain yield agreed fairly well with the observed values. The RMSE, n-RMSE and $r^2$for grain yield were 0.39 t ha^{-1}, 11% and 0.68, respectively. Simulated biomass at crop physiological maturity was also good, given that that the RMSE, n-RMSE and r^2 values were 0.39, 10.2% and 0.66, respectively. In general, the adequacy of relationships between simulated and observed values as evidenced by the low RMSE and n-RMSE values for phenological development, grain yield and biomass production indicated that the model was reliable in reproducing values of observed crop variables across a diverse range of experiments.

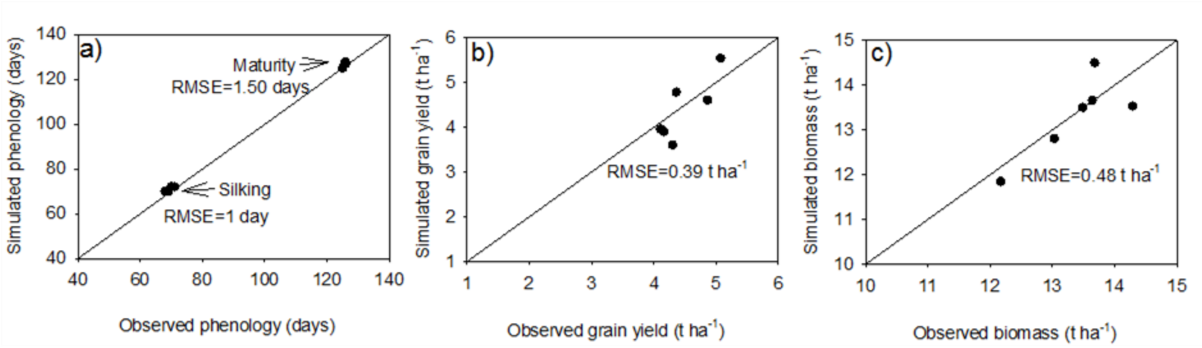


Figure 5.6: Observed and simulated(a) days to silking and physiological maturity; (b) grain yield; and above-ground biomass of cv. *Melkassa-2* from six experiments conducted at Melkassa, Ethiopia (2006–2012). Diagonal lines represent the 1:1 fit where y=x.

5.3.2. Model application

In the simulation scenarios of three sowing windows, the chance for the sowing criterion to be fulfilled increased from May to June to July. Sowing was simulated in only 56% of the 25 seasons when maize was sown in May. Once the sowing criterion was fulfilled, the risk of crop failure due to a false break was less than 5% in May. For June, maize sowing was simulated in 80% of the seasons, and there was no risk of crop failure due to a false break or post-sowing dry-spells. The sowing criterion was always met when the crop was sown in July, and there was a 10% chance of crop failure due to dry-spells.

In any sowing window, the application of N50 produced the greatest increase in median yield compared to the N0 baseline. The response in median yield to increasing the N rate from N0 to N50 was 1.15 t ha^{-1} for May, 1.6 t ha^{-1} for June, and 1.4 t ha^{-1} for July sowing. Further increases in median yield associated with increasing the N rate from N50 to N100 were 0.7 t ha^{-1} for June sowing but smaller (<0.3 t ha^{-1}) for May and July sowing. The maximum median yield was 2.6 t ha^{-1} for May, 4 t ha^{-1} for June, and 3.4 t $ha^{-1}$for July sowing all with the application of N100.

In the analysis, a yield of 2.5 t ha^{-1} was assumed to be the minimum yield that a farmer would attempt to obtain in any given year. The simulations showed that this was only achievable with addition of N fertiliser. The maximum chance of exceeding a yield of 2.5 t ha^{-1} was about 50% for May sowing with either N50 or N100 applied, 64% for June sowing with N50, and 72% for July sowing with N100 (Fig. 5.7).

Overall, yield increases associated with the application of N50 were large (Fig. 5.7). For maize sown in May, the yield obtained with N50 was more than double the yield of unfertilised maize in over 30% of the 25 seasons. There was no benefit from increasing the N rate from N50 to N100 in 64% of the seasons for which sowing in May was simulated as yields were similar at both N rates. For maize sown in June, yields improved in 72% of the 25 seasons with N50 over N0, and with N100 over N50. For July sowing, the application of N fertiliser produced greater yields compared to unfertilised crops in 80% of the seasons. However, a clear yield benefit from increasing the N rate from N50 to N100 was only evident in about 30% of the simulated seasons when maize was sown in July.

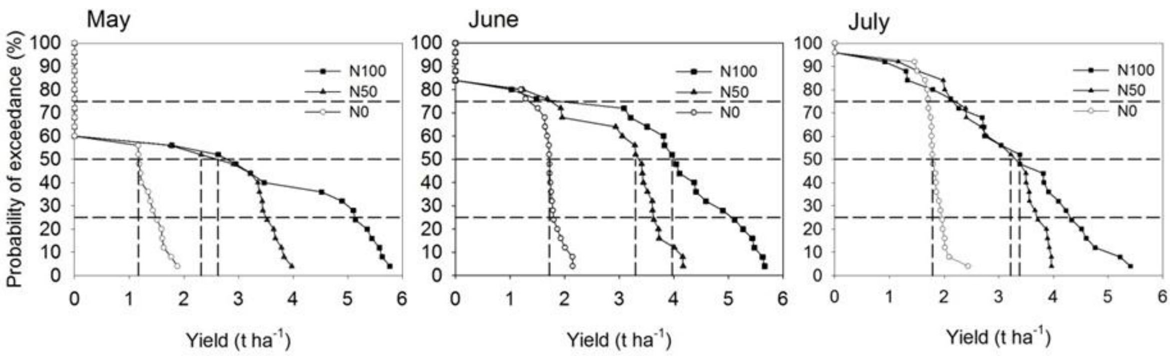


Figure 5.7: Cumulative probability distributions of maize yield (1990–2014) simulated for three sowing windows (May, June, and July) and three nitrogen fertiliser rates (0, 50, and 100 kg N ha^{-1}) at Melkassa, Ethiopia. Horizontal dashed lines represent 25th, 50th, and 75th percentiles and the vertical dashed lines show the median yield for each treatment.

5.4. Discussion

5.4.1. Model performance

Crop phenology is a key trait for modelling because it defines the timing of each developmental event that consequently determines biomass accumulation and partitioning in any given environment (Craufurd et al., 2013). In APSIM, timing and duration of key developmental events of a crop is modulated by water and N stress resulting in delayed phenology when the plant is under limiting abiotic conditions (Saseendran et al., 2008).

This is an improvement compared to its predecessor CERES-Maize, which was only able to simulate maize phenology as a function of thermal time and photoperiod sensitivity under non-limiting N and water-supply conditions (Xie et al., 2001; Gungula et al., 2003; Nouna et al., 2003). The present study showed that the silking and physiological maturity of maize was well simulated for the different sowing dates and N application rates. The error boundaries for silking and physiological maturity appear reasonable and in line with results of other studies (Roman-Paoli et al., 2000; Mavromatis et al., 2001; Gungula et al., 2003). Based on these results, the model was robust in simulating the phenological development of cv. *Melkassa-2,* and APSIM-Maize could be used as a tool to assess maize production with new cultivars in the study area, provided the parameterisation of the cultivar to be used is accurate.

It is a limitation of most crop models that grain yield is overestimated under severe water and N stress conditions (Kiniry, 1991). Among the reasons for this is that effects of severe water stress and nutrient deficiencies on crop growth and phenology are often not sufficiently considered in simulation models (Xie et al., 2001; Gungula et al., 2003; Nouna et al., 2003). However, simulation of these stresses is important to realistically assess time-courses of resource-use and ultimately biomass production and yield (Gungula et al., 2003; Saseendran et al., 2008). Previous studies showed that APSIM-Maize adequately simulates the effect of water and N stress on maize production (Shamudzarira and Robertson, 2002; Song et al., 2010). For the 2012 study at Melkassa, the model overestimated the grain yield of late-sown maize fertilised at 100 kg N ha^{-1}, while above-ground biomass was adequately simulated for this treatment. A reason for this might be that the model did not adequately simulate the detrimental effect of water stress on grain yield of late-sown maize, which may have been intensified by high N supply. The co-limitation of maize yield with N and water availability is a reality in such an environment (NeSmith and Ritchie, 1992; Çakir, 2004; Mueller et al., 2012); however, the model did not reproduce the co-limitation of maize grain yield to the existing environmental conditions (i.e., high N supply and low water availability) in 2012. This may highlight the need to make cultivar-specific adjustments for the combined effects of water stress and high N supply on the growth and development of the various maize cultivars. According to Song et al. (2010), specific experiments are needed to quantify the responses of water stress by the various cultivars to adjust and specify cultivar-specific parameters related to crop growth characteristics in the APSIM-Maize module. This can potentially enhance the model accuracy to simulate relative sensitivity of the cultivars in response to water stress and thus improve the usefulness of the model in providing sound predictions and risk assessment for crop production in semi-arid regions.

Overall, the cascading water-balance model in APSIM simulated the soil water dynamics well demonstrating that the model can be applied in scenario analyses. The model reproduced the temporal variation in soil water contents observed in 2012 well (Fig. 5.3 and 5.4). For example, the large reduction in volumetric soil water due to lack of rainfall at about 100 days after sowing was well captured, particularly for the late-sown maize treatment (Fig. 5.4). However, the simulations were better for early-sown than for late-sown maize. Given that the soil water was parameterised for the 'average soil type', there may be errors related to the spatial variability of the experimental soil causing differences between the simulated and observed soil water contents. The closeness of fit between simulated and measured soil water with an r^2 of0.86 and a RMSE of 0.039 mm mm^{-1}providesconfidence that the model can adequately simulate soil water dynamics for those seasons without measured data.

Crop and soil data from these fields were used to locally parameterise the APSIM model. The statistical measures for evaluating the parameterised model presented here (Tables 5.4 and 5.5; Fig. 5.5 and 5.6) showed that the APSIM-Maize is robust enough to simulate growth, development and yield of maize for local environments in the CRV Ethiopia. For the independent model testing, datasets of maize cultivation that were sown within the normal sowing window in June were used. Given that the experiments at Melkasa were not designed for the purpose of independent model evaluation, the performance of the model was acceptable in terms of reproducing phenological development, grain yield and biomass production. Previous studies showed that APSIM-Maize reliably simulates phenology (RMSE = 1–5 days), grain yield (RMSE = 0.26–0.65 t ha^{-1}) and biomass (RMSE = 0.72–2.26 t ha^{-1}), in a range of water- and N-limited production situations (Thornton et al., 1995; Shamudzarira and Robertson, 2002; Fosu-Mensah et al., 2012; Archontoulis et al., 2014; Kamanga et al., 2014; Araya et al., 2015; Kisaka et al., 2015; MacCarthy et al., 2015). In general, the overall performance of APSIM was good in reproducing observed maize phenology and yield for the different combinations of sowing dates and rates of N fertiliser at the study location. It is therefore clear that the model is robust and can be used successfully as a valuable tool for simulating growth and yield of maize, as well as for understanding of different farmers' strategies and exploring various management regimes that can improve productivity while reducing production risk of the smallholder maize system in the region.

Simulated output of APSIM was validated against farmers' yield records going back 10 seasons from 2002 to 2011. The model, for the specified period, was able to closely reproduce the distribution of average maize yields that were reported by farmers at Melkassa area. Given the fact that there is divergence between the individual farms and the simulated soil types, the model was reasonably accurate in simulating on-farm yields, which was within an acceptable range of accuracy (i.e., <400 kg ha^{-1}). More than 70% of simulated yields were marginally greater than the farmer's actual yield. However, on average, the difference between simulated and actual yields of maize for the Melkassa area was only 140 kg ha^{-1}. Factors unexplained by APSIM simulation (weeds, disease, pest and nutrient deficiencies other than N) might be the key reason in reducing farmers' yield. Therefore, there is a need to further test APSIM using observed experimental data from across locations will help clarify how much of the yield variations described in the farmers yield estimates is attributable to rainfall patterns and N regimes, and to what degree other factors are being considered (Dimes et al., 2011).

5.4.2. Scenario analyses

The simulation analysis of 25 cropping seasons (1990–2014) showed that farmers at Melkassa would benefit from the application of N50 irrespective of the sowing date as demonstrated by large shifts in cumulative distribution functions towards greater yields with N50 over N0 (Fig. 5.7). The latter (N0) is common practice in farming systems in the area where farmers have adopted conservative, risk-averse management approaches in light of highly variable and frequently deficient rainfall (Dimes et al., 2011; Dixit et al., 2011). Many researchers suggest that recommendations on amounts of N fertiliser to be applied should be geared towards achieving a minimum 'guaranteed' grain yield, and take into account the goals, preferences, and risk attitudes of an individual farmer (Dimes et al., 2011; Dixit et al., 2011; Monjardino et al., 2013). Simulation analyses can assist in identifying the N fertiliser rate required to achieve a 'guaranteed' yield (e.g., 2.5 t ha^{-1} as presented above), and to quantify the risk for an insufficient yield response to N fertiliser due to rainfall deficits (Shamudzarira and Robertson, 2002; Moeller et al., 2008, 2014).

In the CRV of Ethiopia, many farmers practice flexible sowing dates depending on the onset of the seasonal rain. Many farmers practice early sowing at the earliest possible time when the rain onsets in the *Belg* season, nevertheless, the crop sown during this time may be at risk of total failure as a result of a false start of rain or intermittent dry-spells occurring later at the critical flowering or grain-filling stages (Kassie et al., 2013a). In general, sowing maize in June is common practice in the Melkassa area (ICRA, 1999) as farmers consider June rainfall to be reliable and stable enough for successful germination and crop establishment. In the simulations for all sowing opportunities in June, there were no crop failures due to dry-spells/false breaks, and the positive shifts in yield distributions associated with applications of N50 and N100 were large in most seasons. Overall, risk was low in the majority of years for which June sowing was simulated. However, sowing was not simulated in 20% of the cropping seasons because of insufficient soil moisture in the upper soil layer where the seed is placed (at least 80% of plant available water in 0–0.15 m depth in the simulations). In years where there is no June sowing opportunity, farmers in the Melkassa area are unlikely to sow any maize as the traditional maize cultivars that many farmers grow are late-maturing and require about 145 days to reach maturity (Ransom et al., 1997; ICRA, 1999). For such cultivars, any delay in sowing until late June or July increases the risk of severe yield reductions or crop failure due to terminal drought, as late-maturing maize flowers and fills grain in September when seasonal rainfall is increasingly erratic. Thus, if a maize sowing opportunity does not occur in June, farmers establish wide furrows along contour lines to capture and harness any rainfall for subsequent sowing of short-duration crops such as tef (*Eragrostis tef* [Zucc.] Trotter) and common bean (*Phaseolus vulgaris* L.).

In the simulations of the July sowing window, a sowing opportunity occurred in every season but the risk of crop failure due to post-sowing rainfall deficits increased to 10%. For a risk-averse farmer, this might be sufficient reason to prefer sowing in June with less sowing opportunities but no, or minimal, risk of crop failure (as discussed above). In the simulations, a medium-maturing maize cultivar requiring about 125–130 days to reach maturity was used (Bogale et al., 2011). To sow such a medium maturity-type is arguably less risky in terms of the likelihood of terminal drought than growing a traditional, late-maturing cultivar requiring about 150 days (Ransom et al., 1997; ICRA, 1999; Nigussie et al., 2001). The simulation results obtained for the medium maturity-type revealed similar yield distributions for both June and July sowing with N0 and N50 suggesting that growing an early/medium maturing maize cultivar in July could be an additional option for farmers. Relations between sowing date and cultivar maturity-type could be further explored in terms of risk and productivity for the region using APSIM-Maize.

Farmers in the Melkassa area perceive sowing in May as too risky. The simulations showed that sowing could be warranted in a limited number of seasons with sufficient soil moisture in the seeding layer, though there was some risk of crop failure (5%) due to post-sowing water deficits. The maximum median yield was the lowest with May sowing (2.6 t ha^{-1} compared to ≥3.4 t ha^{-1} with June/July sowing), which can be explained by greater risk of dry-spells and periods with low in-season rainfall which reduces the efficiency with which fertiliser N is used by the crop to produce grain yield (Akponikpè et al., 2010). Overall, the May sowing window was least desirable in terms of risk and productivity.

The yield estimates and likely occurrence provided by farmers for the good, average and bad seasons at the study area of Melkassa out of every ten years were compared against the simulated yield at 10^{th}, 50^{th} and 90^{th} percentiles, respectively. The simulations were run retrospectively each year from 1982–2011 for the defined June sowing opportunity at Melkassa. Much of the simulated yield distributions did conform to locally expected ranges of yield for given season types. However, more than two-third of the interviewed farmers estimated that crop failure is ~20% likely at Melkassa while the simulated yields suggest that the probability is only 5%. This simply shows that farmers do over-estimate the frequency of unfavourable seasons. In general, the result provides confidence for effectively use APSIM in making strategic management decisions on real farms.

It was clear that an understanding of climatic risks and their interaction with crop management decisions could be considerably enhanced via modelling and simulation capability so that the likely risk consequences of management decisions can be effectively explored. To that effect, crop simulation models can provide probabilistic estimates of yield for a range of decision options, such as sowing time, cultivar maturity and N fertiliser management, evaluated under various soil types and climatic conditions. Adapting desirable sowing date, cultivar type and N fertiliser management are some of the key agronomic practices often available to positively influence resource-use efficiency of the major crops grown in environments limited by soil water and N resources, hence improving the production level and risk of the smallholder cropping systems under situations of climate risks and uncertainties.

5.5. Conclusion

The study showed that APSIM-Maize is able to simulate crop phenology, grain, and biomass yield, as well as the soil water dynamics reasonably well under a range of production situations in the semi-arid study environment. This was supported by statistical measures of model performance. The scenario analyses highlighted the importance of N fertiliser supply for productivity, which is not a standard practice in the study region. Adjusting the sowing window to match the cumulative crop-water demand to seasonal rainfall supply is important for reducing the production risk. However, there may be further opportunities for risk reduction and productivity increases by sowing cultivars of varying maturity-type depending on the expected length of the rainy season. This aspect warrants further analysis. Crop simulation is a cost-effective way of exploring "what if" options and formulating alternative management strategies. The approach can assist farmers and their advisors in making better informed decisions in environments where climate-related risks and uncertainty are high.

Chapter 6 Risks and benefits associated with alternative management practices in maize systems of smallholder farmers in semi-arid environments of Ethiopia

Abstract

Maize (*Zea mays* L.) production in the CRV region of Ethiopia is influenced by high inter- and intra-seasonal variation in timing and amount of rainfall and periodic water stress. There is a need to develop management interventions and assess whether these are effective in designing production systems that are sustainable and resilient in the face of varying and changing climate. Crop models as research or decision tools, can assist researchers, extension advisors and farmers to evaluate a range of agronomic and technological options that can adapt to the varying seasonal climate and socio-economic settings of the targeted smallholder farming systems. As the APSIM-maize model could capture the grain yield of maize under the various management practices and weather conditions (Chapter 5), the various scenarios were simulated after configuring APSIM-Maize to conduct retrospective analysis of the maize system at Adamitulu and Melkassa locations in the CRV region. Using the long-term simulations, key factors that the participating farmers identified as important for determining their agronomic decisions were evaluated for their effectiveness in enhancing crop productivity while reducing the likely chance of production risk under seasonal climate variations and uncertainties (Chapter 3). Therefore, the study used APSIM-Maize for assessing impacts of climate and selected agronomic practices on simulated maize yield for varying sowing dates (early [March–May], normal [1–15 June] and late [16–30 June]), phenotypes (early-, medium- and late-maturing cultivars) and N rates (0, 25 and 50 kg N ha^{-1}). In the scenario analyses using 34–39 years of local weather data from the meteorological stations close by the study villages, the typical local farmers' management practices were compared with the agronomic recommendations from research and extension services. A range of factorial combinations of the three agronomic management choices (3 sowing window x 3 cultivar type x 3 N rates of fertiliser x 2 locations = 54 simulation scenarios) were compared so that management recommendations best suited to the local bio-physical and specific socio-economic conditions at the study environment could be determined. The risk of crop failure at the study areas were more likely to occur with early sowing than with normal or

late sowing as a result of the false start of rain or a risk of post-sowing dry-spells. The chance of crop failure as well as achieving less than the minimum threshold yield (2–2.5 t ha^{-1}) is lower if either the medium or the late cultivar was sown in the normal to late sowing window than in the early sowing window. Across all sowing times and rates of N fertiliser, farmers would be better off sowing the late cultivars with high yield gains in most years with less likelihood of crop loss compared with sowing the other cultivars, except for the late sowing window at Adamitulu where the chance of crop failure is greater than sowing the medium cultivar. The farmers would achieve a considerable benefit in the long-term if they opt to select late-maturing cultivar in average to high yielding years, regardless of sowing time and rates of N fertiliser. There was a rare case that the early-maturing cultivar did result in yield gain over the medium or late cultivar regardless of the sowing dates and rates of N fertiliser. Typical farmers in the CRV region do not usually apply N fertiliser at all. However, if the majority of the risk-averse farmers in the region were encouraged to invest in N fertiliser input at a modest rate of 25 kg N ha^{-1}, they could raise the median yield by at least 45%, compared to the yield at zero rate of N fertiliser, without inducing additional risk of crop failure or increasing the inter-seasonal variation in maize yield. Compared to the farmer baseline N application strategy, the locally recommended rate of 50 kg N ha^{-1} can be expected to have negative effects on yield in as much as 20% of the seasons. On the other hand, a yield advantage at 50 kg N ha^{-1} of more than 70% relative to zero N application could be achieved in at least 85% of the simulated seasons, regardless of sowing time and cultivar type. Farmers in the semi-arid environment should be provided with information about the likely production risk associated with the various agronomic and technological interventions with a view to better managing climate risk and efficiently using the limiting N and water resource in the semi-arid region of Ethiopia. Adapting this kind of systems approach as a means of addressing problems posed by the farmers will be successful for identifying appropriate agronomic strategies for the smallholder farming systems that can enable farmers to successfully overcome the prevailing low production, low profitability and high-risk problems associated with a high climate uncertainty.

6.1. Introduction

Smallholder maize (*Zea mays* L.) farmers in the CRV region of Ethiopia try to manage rainfall variability by adjusting the sowing date, cultivar maturity-type, and the timing and amount of fertiliser application. Farmers make these agronomic decisions in response to the actual and expected seasonal rainfall. However, local research and extension services often promote fixed agronomic management practices (i.e., a single, or narrowly defined, sowing date, cultivar type, fertiliser rate), which do not account for seasonal rainfall conditions and expected yield potential (Fujisaka et al., 1996a; Admassu et al., 2014). Prescriptive agronomic recommendations that are the same for all season types are unrealistic in a region where farmers sow maize in response to what they perceive as the onset of the rainy season, and where they sow maize cultivars of varying maturity depending on the onset of rains (Admassu et al., 2014).

In semi-arid tropics, the consequences of any agronomic decisions made at sowing are uncertain (Muchow et al., 1994), however, many farmers sow with the first rains to capture the flush of mineralised soil N (Weber, 1995), and to benefit from a long growing season to maximise crop yield (Jagtap and Abamu, 2003; Sacks et al., 2010). Whether farmers in the CRV of Ethiopia sow their maize early in the *Belg* season (March to April) or later in the *Kiremt* season (June), they always face the challenge of risky choices that can result in low yield. Farmers who sow early encounter a high chance of post-sowing dry-spells at crop establishment, while farmers who sow late may lose yield because of soil water deficits towards the end of the season (Diga, 2005). The length of the growing season in the CRV of Ethiopia generally varies from season to season, and there is a high correlation between the date of the seasonal rainfall onset and the length of the growing season (Kassie et al., 2013b). Therefore, the cultivar choice should also fit the effective length of the rainy season in order to achieve a high yield (Kamara et al., 2009). The greater the deviation of the timing of sowing from the optimum sowing date for a particular cultivar type, the greater the yield loss will be (Berzsenyi and Lap, 2001; Beiragi et al., 2011). If better information is provided to farmers and extension agents on how the sowing window and choice of cultivar affect grain yield, the gain in yield of maize can be significantly improved. However, the effect of varying sowing dates on maize productivity and production risks has not been properly evaluated in the CRV of Ethiopia. Farmers can make informed decisions by taking into account the yield variations that can be expected based on the timing of sowing and the cultivar type in light of climate variability (Jagtap and Abamu, 2003).

In the semi-arid region of Ethiopia, soils are inherently low in plant-available N (Biazin and Stroosnijder, 2012). For this reason, the amount and timing of N fertiliser applications has been a major focus of agronomic research aimed at improving yields in smallholder farming systems (Reddy and Georgis, 1993; Senay and Verdin, 2003). Where rainfall variability is high, the yield response to available soil N and N fertiliser is strongly variable as well (Muchow, 1991; Keating et al., 2000; Roxburgh and Rodriguez, 2016). In addition to its high cost, there is a risk of a yield response that is often insufficient to recoup the fertiliser investment. Therefore, smallholder farmers are often reluctant to use the recommended rate of N fertiliser; they generally favour low-risk investment in fertiliser input so that they often miss out on the opportunities created by better seasonal conditions (Dimes, 2011; Roxburgh and Rodriguez, 2016). On the other hand, farmers' decisions can be guided if the extension services are able to provide information on the risk of poor yield responses, and highlight the opportunities related to investment in N fertiliser in light of climate variability and uncertainty (Whitbread et al., 2010; Dimes, 2011). If farmers are to realise potential yield gain in crop productivity, they also need to be advised on N fertiliser application with matching good agronomic practices, most notably timely sowing and suitable cultivar type so that the agronomic use efficiency for the limited use of N fertiliser can be maximised (Xu et al., 2009; Tittonell and Giller, 2013; Kassie et al., 2014; Getnet et al., 2016).

One of the limitations of using results from traditional agronomic experiments is associated with the variable response of the tested agronomic factors from season to season and across sites (Dixit et al., 2011; Stern and Cooper, 2011). Moreover, long-term field experiments are costly and difficult to achieve (Muchow et al., 1991). Given the difficulties of field experiments in capturing the highly complex and nonlinear responses of the crop and the dynamics of soil processes, crop simulation and modelling is both a time and cost effective approach for quantifying interaction effects, such as climate variability, changes in agronomic management and/or genetics (GxExM) on resource productivity and crop yields (Keating et al., 2000; Cooper et al., 2008; Van Ittersum et al., 2013; Kassie et al., 2014). Based on the simulated output, better agronomic practices and technological recommendations can be formulated for advising the local extension services in assisting farmers' decisions under climate risk and uncertainty (Van Ittersum and Rabbinge, 1997; Keating et al., 2000; Shamudzarira et al., 2000; Dimes, 2011). APSIM has been widely tested and used to better manage climate risk and resource (e.g., N and water) limitations in maize production systems, including those in the semi-arid regions of sub-Sahran Africa (SSA) (Keating et al., 1994; Shamudzarira et al., 2000; 2010; Kamanga et al., 2014; Kisaka et al., 2015). This makes APSIM an appealing analytical and decision support tool for application in SSA (Kamanga et al., 2010 and 2014; Kisaka et al., 2015).

In this study, APSIM-Maize was used to evaluate and compare maize management strategies (timing of sowing, cultivar maturity-type, and N fertiliser rate) proposed by research and extension professionals with those used by farmers. Long-term simulation scenarios were used to assess maize yield variability using historical weather data from two locations in the CRV of Ethiopia. The objectives of the scenario simulations were to evaluate local farmer management strategies previously identified as being important in smallholder maize systems (Chapter 3) and those recommended by research and extension services, and to quantify production risks and benefit in yield gain associated with the various combinations of management factors.

6.2. Materials and methods

6.2.1. Model configuration

The parameterisation and evaluation of APSIM is detailed in Chapter 5. The model satisfactorily simulated maize responses (e.g., phenology, grain yield and biomass) to various management (different N application rates and sowing dates) and seasonal conditions in the study environment. This showed that the model is credible for subsequent application in the long-term simulation scenarios to assess the risks associated with different agronomic management practices. For the simulation scenarios, APSIM was configured to simulate the maize system and to explore key drivers of yield response as modified by the different management options (sowing dates, cultivar choice, and rates of N fertiliser applied). Simulations were run for two locations in the CRV region of Ethiopia.

6.2.2. Weather data

Daily weather data were available from Adamitulu (1982–2015; 7°50' N and 38°40' E, 1690 m elevation) and Melkassa (1977–2015; 8°24' N, 39°12' E, 1550 m elevation). Adamitulu and Melkassa have an average annual rainfall of 811 mm and 825 mm, and average annual temperature of 20.7°C and 21.2°C, respectively. The study area has a bi-modal rainfall pattern. The short rainy season (March–May) is locally called the *Belg* season. *Belg* rainfall varies from 91 mm to 454 mm (CV = 48%) at Adamitulu (1982–2015), and from 53 mm to 382 mm (CV = 45%) at Melkassa (1977–2015). The long rainy season (June–September) is known at the *Kiremt* season. *Kiremt* rainfall ranges from 311 to 894 mm (CV = 30%) at Adamitulu, and between 291 mm to 829 mm (CV = 21%) at Melkassa. On an annual basis, rains start between March and April, peaks between July and August, and ends in September (Kassie et al., 2014).

6.2.3. Cultivar parameters

Cultivar parameters of development, phenology and crop growth for the medium-maturing maize cultivar *Melkassa-2* (130 days from sowing to maturity) were derived from field experiments conducted in 2012 at Melkassa as part of the study (Chapter 5; Table 5.2). *Melkassa-2* is well-adapted and grown widely by smallholder farmers in the CRV of Ethiopia. In this study, cultivar parameters for the locally adapted late- and early-maturing cultivars were not derived; nor had the descriptions for their phenological duration and yield been previously modelled with APSIM. Therefore, the default cultivar parameters from similar cultivars that are available in the crop library of APSIM-Maize were used to represent those specified cultivars for the long-term simulation scenario. The late-maturing cultivars, cv. *Hybred 614* (a cultivar from Kenya requiring 145 days from sowing to maturity) (Benson, 1999) and cv. *SC709* (a cultivar from Zimbabwe requiring 140 days from sowing to maturity) (Dimes et al., 2011) were used. Early-maturing maize was represented by cv. *Pan 6671*(110 days from sowing to maturity) (Murovhi and Materechera, 2013). The different sets of parameters that define the phenology, crop growth and yield of the four cultivars were specified in the Table 6.1. More detailed descriptions of the parameter sets in simulating the specific cultivars included in the APSIM v7.5 release can be found at the APSIM website: http://www.apsim.info.

Table 6.1: APSIM-Maize parameters to simulate cultivars differing in phenology at Adamitulu and Melkassa.

cultivars parameters	*Hybred614*	*SC709*	*Melkassa-2*	*Pan6671*
tt_emerg_to_endjuv (thermal time required from emergence to end of juvenile (^oCd))	365	250	230	200
tt_flower_to_maturity (thermal time required from flowering to maturity (^oCd))	740	980	730	710
tt_flower_to_start_grain (thermal time required from floweringto starting grain-filling (^oCd))	70	120	170	160
Head_grain_no_max (maximum grain numbers per ear)	650	650	450	450
Grain_gth_rate (grain growth rate (mg grain^{-1} day^{-1}))	10.5	9.2	8	8

6.2.4. Sowing management

Three sowing windows (Adamitulu: 1 March–30 May, 1–15 June and 16–30 June) and (Melkassa: 1 April–30 May, 1–15 June and 16–30 June) were specified for each location (Table 6.2). They are subsequently referred to as early, normal, and late sowing. In all cases, sowing time was controlled by the same sowing rule within the window in the model. That is, sowing was simulated when there was an accumulation of 25 mm of rainfall over five consecutive days, and when the soil water content in 0–0.15 m depth exceeded 80% of the plant available water-holding capacity (PAWC) of that soil layer. The sowing criteria for the above-specified rainfall rule and stored soil water to initiate sowing within the sowing window was chosen to ensure that crops would germinate after sowing and to maintain the crop if conditions turned dry. The sowing rule is also assumed to represent the farmers practice for sowing their crop. In the simulations, the plant density was set to 6.7 plants m^2, and the sowing depth and row spacing were 0.06 m and 0.75 m, respectively.

6.2.5. Soil properties

The properties (PAWC, soil N and C status) of a typical calcareous clay loam of volcanic parent material classified as a Typic Haplustand soil characterised in a field experiment conducted at Melkassa in 2012 were used for the model application (Chapter 3; Table 3.1).

The PAWC of the soil was 218 mm in 0–1.20 m soil depth (Chapter 4; Fig. 4.1). In every year, on the simulated sowing date, available mineral N (NO_3) was set to the starting conditions, i.e., 40 kg N ha^{-1} in 0–1.20 m soil depth as measured at the experimental plot when maize was sown in the 2012 season (Chapter 5; Fig. 5.2). The amount of maize surface residue (C: N ratio = 80) was similarly initialised at 0.5 t ha^{-1}. The annual resetting of the above soil parameters to the specified initial values was implemented on nominated sowing date so that the seasonal weather was the major factor to affect maize growth and yield under different management scenarios. Moreover, it prevents the effects of carry-over errors from the previous seasons to the next that would reduce the accuracy of model.

6.2.6. Nitrogen application

In the simulations, N fertiliser was applied as urea-N at rates of 0 kg N ha^{-1} (N0), 25 kg N ha^{-1}, (N25) and 50 kg N ha^{-1} (N50). For the fertilised treatments, a maximum of N25 was applied at sowing. For the N50 treatment, a second rate of N25 was applied 35 days after sowing. All nutrients other than N, and the effects of damage by pests, disease and weeds were not modelled and assumed to be non-limiting.

6.2.7. Long-term simulation scenarios

APSIM was configured to investigate yield benefit, variation in yield response, as well as risk of crop failure as modified by the effects of sowing dates, cultivar choice and rates of N fertiliser. Simulations of maize yield were run for a period of 34 years (1982–2015) and 39 years (1977–2015) using daily weather data from Adamitulu and Melkassa meteorological stations, respectively. In the simulations, only the parameterised soil at Melkassa was used to represent both locations, which is one of the typical soils in the region. Simulated yield was reported at 12.5% moisture content. Further details of management scenarios for the local farmers' management practices and agronomic recommendations from extension services, along with alternative management scenario representing other agronomic measures, are described below in Table 6.2. In some cases, the long-term simulations spanned three of the above management scenarios, allowing variation in yield response resulting from the interactions of key agronomic factors to be explored. The long-term simulations involve three sowing windows (early [March/April–May], normal [1–15 June] and late [16–30 June]), three phenotypes (early-, medium- and late- maturing cultivars) and three N rates (N0, N25 and N50)). In total, the different simulated combinations for three agronomic factors at two locations (3 sowing windows x 3 cultivars x 3 N rates of fertiliser x 2 locations) resulted in 54 scenarios for analysis.

Scenario 1: baseline of local farmer practices

This scenario was set up to simulate the conventional farming practices of smallholder farmers and to simulate the agronomic management practices extension services advise farmers to implement in the semi-arid region of Ethiopia. Farmers' sowing decisions are flexible and vary with the onset of seasonal rainfall. Cultivar choices depended on the opening rains of the season. Early sowing of a late-maturing cultivar represented what farmers would choose to do when rains start in the *Belg* season between March and May in Adamitulu and between April and May in Melkassa. If rain starts in the *kiremt* season in June, they opt to sow either a medium-maturing cultivar in early- to mid-June or an early-maturing cultivar when rains are very late until the end of June. The zero rate of N (N0) treatment represented the baseline scenario for typical farmers who are resource-poor and cannot afford to invest in commercial fertiliser. The N25 treatment represents a conservative N fertiliser strategy used by few farmers, and it is less than the recommended N rate that is promoted by the local extension services for the CRV region.

Scenario 2: management recommended by extension services

A sowing window recommended by research and extension services was included for medium and early cultivars. The extension service recommendation is to sow when rains are assumed to be reliably established in June, i.e., sow medium-maturing cultivars between 1–15 June, or else sow an early-maturing maize cultivar between 15–30 June. A blanket recommendation of 50 kg N ha^{-1} was split into two applications, 25 kg ha^{-1} applied at sowing and the remainder at 35 days after sowing. The N50 treatment was assumed in representing the maximum amount that risk-bearing farmers would apply to their maize field.

Scenario 3: alternative management strategies

In addition to the above management scenarios, other variations to agronomic factors, which are different from both what is currently practiced by local farmers and what is recommended by extension services, were also explored.

Table 6.2: Description of simulation scenarios (combinations of sowing window, cultivar type, and N fertiliser rate) for Melkassa and Adamitulu: typical agronomic practices employed by smallholder farmers (1), agronomic recommendations of extension services (2) and alternative management measures (3).

1. Farmers' management practices	
Early sowing	***Adamitulu*** *Sowing window(1 March–30 May); LM cultivar (145 d to mature); N fertiliser level (0 and 25 kg N ha^{-1})* ***Melkassa*** *Sowing window (1 April–30 May); LM cultivar (140 d to mature); N fertiliser level (0 and 25 kg N ha^{-1})*
Normal sowing	*Sowing window (1–15 June); MM cultivar (130 d to mature); N fertiliser level (0 and 25 kg N ha^{-1})*
Late sowing	*Sowing window (16–30 June); EM cultivar (110 d to mature); N fertiliser level (0 and 25 kg N ha^{-1})*
2. Agronomist/extension recommendation	
Normal sowing	*Sowing window (1–15 June); MM cultivar; N fertiliser level (50 kg N ha^{-1})*
Late sowing	*Sowing window (16–30 June); EM cultivar; N fertiliser level (50 kg N ha^{-1})*
3. Alternative management options	
Early sowing	*Factorial combinations of EM and MM cultivars and N fertiliser level (0, 25 and 50 kg N ha^{-1})*
Normal sowing	*Factorial combinations of LM and EM cultivars and N fertiliser level (0, 25 and 50 kg N ha^{-1})*
Late sowing	*Factorial combinations of LM and MM cultivars and N fertiliser level (0, 25 and 50 kg N ha^{-1})*

LM=late maturing, MM=Medium maturing, EM=early maturing

6.2.8. Statistical analysis and assessment of risk

In this study the production risk was assessed from the probability distributions of maize grain yields to quantify the possible consequences or outcomes (Cross, 2000). In particular, the production risk associated with various management factors (sowing window, cultivar type and N fertiliser) was assessed by the probabilities of risks of crop failure (the probability of yield being zero), of achieving median yields, and of falling short of "threshold" yield levels of 2.2 t ha^{-1} at Adamitulu and 2.5 t ha^{-1} at Melkassa. The threshold yields that a typical farmer would expect in any given year were assessed during the survey of the study locations (Chapter 3; Table 3.4).

To test the hypothesis that there are treatment differences and interactions between sowing window, cultivar type, and N application, the simulated grain yields were analysed in an unbalanced analysis of variance (ANOVA) using GenStat statistical package (14^{th} edition; VSN International, 2011). The factors 'sowing window', 'N fertiliser rate', and 'cultivar' were included in the model, and three-way interactions between these main effects were assessed. Analysis of variance tests of the long-term simulations used each year as a replication.

Effects due to years were considered a random factor, while all other factors were treated as fixed effects. The combined crop yield data for the two locations was analysed using the REML subroutine in GenStat. In the REML analysis, both fixed and random factors were included to account for more than one source of variation in the data and provide estimates for treatment effects in unbalanced treatment designs. Location was included in the fixed model so that differences between locations could be tested. Combined analyses enabled the determination of location x treatment interaction effects, and the analysis resulted insignificant location x sowing x cultivar ($P = 0.002$) and location x sowing interactions ($P < 0.001$), suggesting that sowing was location dependent. Due to a significant lack of homogeneity of variance across the two locations, data were treated as independent from the locations and analysed separately.

The co-efficient of variation (CV%, calculated as a ratio of the standard deviation to the mean yield multiplied by 100) was used as a measure of mean inter-seasonal variation in grain yield, as well as to assess risk of maize production in terms of factors that contributed most to inter-annual yield variability.

The Kolmogorov-Smirnov (K-S) test was applied to determine significant differences between the cumulative distribution functions (CDFs) of yield obtained with different management practices as described above (Hassani and Silva, 2015). The K-S test calculates if the CDFs differ significantly in terms of the maximum vertical distance between the two CDFs. The K-S test is non-parametric and has the advantage of making no assumption about the data distribution.

6.3. Results

Rainfall from sowing to harvest was recorded every year as in-crop rainfall. Figure 6.1 illustrates the variation in the in-season rainfall for the simulated years in the simulation scenarios. The variability in seasonal rainfall was higher at Adamitulu than at Melkassa across the simulated years.

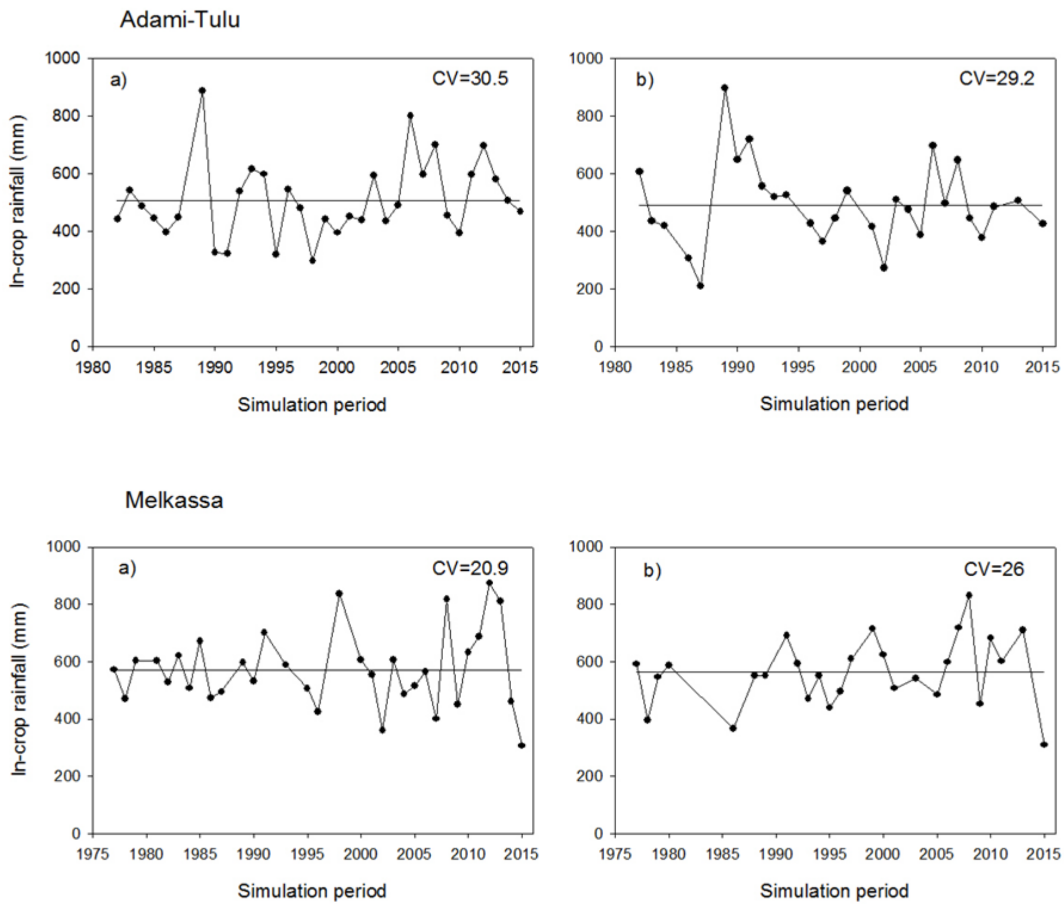


Figure 6.1: In-crop rainfall amounts over the simulation period for early sowing (1 March–30 May) at Adamitulu and (1 April–30 May) at Melkassa (a) and for normal and late sowings (1–30 June) at both locations (b). The horizontal lines inside the figures are the long-term average in-crop rainfall amounts for the simulated seasons.

6.3.1. Interactions between management strategies

There was a 3-way significant interaction between sowing window, cultivar type, and N application ($P < 0.001$) at each study location. The sowing time by cultivar interaction significantly influenced maize grain yield ($P < 0.001$), and this was different between the study locations. At Adamitulu, the grain yield (mean of all N treatments) of the late-maturing cultivar was significantly greater for early sowing with an average yield of 3 t ha^{-1}, which was 15% higher than the normal and late sowing scenarios. On average, grain yield of the late-maturing cultivar was consistently reduced when sowing was delayed from a normal to late timing scenario (Table 6.3). This was different at Melkassa, where early sowing of the late-maturing cultivar reduced the average yield by 29% compared to normal and late sowing of the late-maturing cultivar (2.8 vs. 3.6 t ha^{-1}) (Table 6.4). For the early sowing scenario, the average yields of the early- and medium-maturing cultivars were reduced by 41–50% at Adamitulu, and by 26–33% at Melkassa, when compared to normal and late sowing. The average grain yield of the medium- and early-maturing cultivars at Adamitulu were similar when they were sown either at a normal or late sowing date, while the yields at Melkassa increased by at least 15% when sowing was delayed from a normal to late timing (Tables 6.3 and 6.4).

There was a significant interaction between the effects of cultivar and N rate ($P < 0.001$). At both locations, the average yields (mean of all cultivars) increased by 96–120% when N50 was applied, and by 41–56% with N25 compared to unfertilised maize (Tables 6.3 and 6.4). The application of N fertiliser increased maize grain yield, and this increase was greatest, on average, for the late-maturing cultivar irrespective of the sowing window. At Adamitulu, grain yield of the late-maturing cultivar responded similarly to N0 across all sowing windows, while the average yields for the early sowing date were greater with N25 (10–20%) and N50 (23–48%) application than the normal or late sowing date. At Melkassa, selecting a late-maturing cultivar resulted in >50% more yield with N0 and 20–32% more yield with either N25 or N50 at normal or late sowing, relative to early sowing. The grain yield response of the late-maturing cultivar grown with N25 was equal to that of the medium and the early-maturing cultivars grown with N50, compared in the early sowing scenario at Adamitulu, and in the normal and late sowing scenarios at Melkassa.

There were significant sowing time x N rate x location interactions ($P < 001$), showing the effect of N fertiliser availability on sowing time differed between the two locations. Independent analysis for each location showed that sowing time by N application rate interactions were significant at Adamitulu ($P < 0.001$), but not at Melkassa. Grain yields (mean of all cultivars) from early and late sowing scenarios were more responsive to N fertiliser at Melkassa than at Adamitulu, however, grain yields (mean of all cultivars) in the normal sowing scenario were more responsive to N fertiliser at Adamitulu than at Melkassa. Across the sowing windows at both locations, each cultivar grown with a high N rate out-yielded those grown with a low N rate ($P < 0.01$); however, yield was more responsive to N fertilisation when the late cultivar and early sowing, and the medium and early cultivars at normal sowing, were selected.

Table 6.3: Minimum, average, median, maximum, and coefficient of variation (CV %) of simulated maize grain yields for different sowing windows (early: 1 March–30 May; normal: 1–15 Jun; late: 16–30 Jun), cultivar types (early, medium and late maturing), nitrogen (N) fertiliser rates (0, 25, and 50 kg N ha^{-1}) at Adamitulu.

Sowing window	Cultivar	Minimum yield (t ha^{-1})			Average yield (t ha^{-1})			Median yield (t ha^{-1})			Maximum yield (t ha^{-1})			CV%		
		N0	N25	N50	N0	N25	N50	N0	N25	N50	N0	N25	N50	N0	N25	N50
Early	Late	0.0	0.0	0.0	1.8	3.0	4.3	1.9	3.1	4.9	3.4	4.6	6.0	36.7	35.3	41.6
	Medium	0.0	0.0	0.0	1.0	1.7	2.1	0.9	1.8	1.9	2.1	3.0	4.5	58.9	60.1	67.6
	Early	0.0	0.0	0.0	0.9	1.4	1.8	0.7	1.2	1.2	2.3	3.0	4.3	76.7	78.6	87.0
Normal	Late	0.0	0.0	0.0	1.7	2.7	3.5	2.0	3.3	4.0	2.9	4.4	5.7	23.9	24.9	25.0
	Medium	0.0	0.0	0.0	1.3	2.2	3.0	1.5	2.5	3.5	2.0	3.1	4.2	28.5	27.3	27.4
	Early	0.0	0.0	0.0	1.1	1.9	2.8	1.3	2.2	3.3	1.9	3.0	4.2	18.7	20.3	20.4
Late	Late	0.0	0.0	0.0	1.7	2.5	2.9	1.8	2.7	3.6	3.0	4.3	5.5	23.3	25.4	29.5
	Medium	0.4	0.4	0.4	1.4	2.2	2.9	1.5	2.4	3.1	2.3	3.4	4.6	18.7	20.3	20.4
	Early	0.7	0.4	0.4	1.2	2.1	2.8	1.3	2.2	3.1	1.9	3.1	4.2	19.9	19.6	20.1

N0: 0 kg N ha^{-1}; N25: 25 kg N ha^{-1}; N50: 50 kg N ha^{-1}

Table 6.4: Minimum, average, median, maximum, and coefficient of variation (CV %) of simulated maize grain yields for different sowing windows (early: 1 April–30 May; normal: 1–15 Jun; late: 16–30 Jun), cultivar types (early, medium and late maturing), nitrogen (N) fertiliser rates (0, 25, and 50 kg N ha^{-1}) at Melkassa.

Sowing window	Cultivar	Minimum yield (t ha^{-1})			Average yield (t ha^{-1})			Median yield (t ha^{-1})			Maximum yield (t ha^{-1})			CV%		
		N0	N25	N50	N0	N25	N50	N0	N25	N50	N0	N25	N50	N0	N25	N50
Early	Late	0.5	0.2	0.1	1.6	2.9	3.7	1.9	3.2	4.5	2.7	4.2	5.6	53.9	41.4	43.8
	Medium	0.0	0.0	0.0	1.1	1.8	2.4	1.2	2.3	2.5	2.3	3.5	4.8	66.6	53.4	62.7
	Early	0.0	0.0	0.0	0.8	1.4	1.8	0.9	1.5	1.6	2.0	3.2	4.5	92.3	83.7	93.3
Normal	Late	0.6	0.5	0.5	2.4	3.6	4.7	2.6	3.8	5.0	3.1	4.4	5.5	45.8	46.6	48.5
	Medium	0.0	0.0	0.0	1.7	2.7	3.8	1.9	3.0	4.0	2.1	3.2	4.6	39.4	37.8	38.5
	Early	0.4	0.0	0.0	1.4	2.3	3.3	1.5	2.5	3.6	1.9	2.9	4.0	41.1	42.8	44.9
Late	Late	0.5	0.3	0.3	2.7	3.8	4.5	2.7	4.0	4.7	3.2	4.6	5.8	62.3	54.9	47.3
	Medium	0.6	0.4	0.6	2.6	3.0	4.0	2.0	3.1	4.1	2.3	3.4	4.8	41.2	35.8	36.3
	Early	0.5	0.5	0.5	1.7	2.6	3.7	1.7	2.5	3.7	2.2	3.4	4.6	39.5	34.3	31.3

N0: 0 kg N ha^{-1}; N25: 25 kg N ha^{-1}; N50: 50 kg N ha^{-1}

6.3.2. Farmers' management

The consequences of sowing decisions made when a sowing opportunity occurs are uncertain unless the chance of successful sowing and the risk of crop failure was analysed for each sowing window. Early sowing of a late-maturing cultivar represents what a typical farmer would choose to do when rains start early in March at Adamitulu and in April at Melkassa. For the early sowing window, the chances of successful sowing, after sowing criteria being met, were greater at Adamitulu than at Melkassa (85 vs. 97% of all years). The risk of crop failure due to a false break (when the firsts rain was followed by dry-spells causing seedling death) or prolonged dry-spells at later growth stages was assessed for an early sowing strategy. Early sowing of a late maturing cultivar caused crop failure in 10% of all years at Adamitulu, while the model simulated no risk of crop failure at Melkassa. For the normal (1–15 June) and late (16–30 June) sowing window, farmers could use either the late-maturing or medium- to early-maturing cultivars. When following a normal sowing scenario, the likelihood of crop failure was 5% for each year. Crop failure did not occur for the late sowing window, except for the late-maturing cultivar at Adamitulu where there was risk of crop failure in ~15% of all years.

With no N fertiliser applied to a late-maturing cultivar sown early, i.e., before 1 June (Table 6.2), the chance of obtaining a threshold yield of 2.2–2.5 t ha^{-1} was ~30% at Adamitulu and 0% at Melkassa. By sowing the late-maturing cultivar later in June, however, farmers at Melkassa could achieve the threshold yields in 68% of all years, whereas this was only possible in 35% of all years at Adamitulu. Using a typical farmers' strategy of zero N fertiliser application, the targeted 'threshold' yields were unlikely to be achieved across the sowing window when either an early- or medium-maturing cultivar was selected.

For the three sowing windows, median yields of the various cultivars were assessed for the N rate used by the majority of farmers, i.e., N0. For early sowing scenarios, the median yield of late cultivars at N0 (1.9 t ha^{-1}) were the same at both locations. The median yields of late cultivars at N0 (~2 t ha^{-1}) did not differ across the sowing window at Adamitulu, while the median yields at Melkassa increased from 1.9 t ha^{-1} at early sowing to 2.7 t ha^{-1} at later sowings in June (yield gain of +30%). With a medium or early maturing cultivar grown with N0, the long-term median yields did not exceed 1.5 t ha^{-1} at Adamitulu, and 2 t ha^{-1} at Melkassa, irrespective of the sowing window.

6.3.3. Management recommended by extension services

Research and extension services recommend delaying sowing until June (normal sowing from 1–15 June), when rains are likely to be more reliable, and to sow a medium-maturing cultivar with application of N50 (recommended N rate). For a normal sowing scenario, the chance of sowing occurring was 17% greater at Adamitulu than at Melkassa. With late sowing (16–30 June; for which research and extension services advise farmers to sow an early cultivar at the recommended N rate), the sowing rule was met and sowing was simulated in 64% of all years compared to 41–58% of all years using a normal sowing window. At both locations, the likelihood of crop failure with normal or late sowing was not more than 5% of all years. With the application of N50, the chance of achieving threshold yields with a medium-maturing cultivar at normal sowing occurred in 90% of all years, with median yields of 3.5 t ha^{-1} at Adamitulu and 4.0 t ha^{-1} at Melkassa. When an early cultivar was sown late, providing N50 could guarantee farmers threshold yields in 80% of all years at Adamitulu and in >95% of all years at Melkassa, with median yields of 3.1 t ha^{-1} at Adamitulu and 3.7 t ha^{-1} at Melkassa.

6.3.4. Comparison of farmers' strategies and extension services recommendations

Farmer strategies were compared with recommendations made by research and extension services. The sowing preference and cultivar choice define the two strategies, and the management scenarios were assessed using N0 and N50. According to the K-S test, the difference between yield CDFs associated with the farmers' strategy and extension services recommendation was significantly different in distribution at N0 ($P = 0.025$) and at N50 ($P < 0.001$). When comparing the probability distribution, the grain yields obtained with the farmers' strategy was greater in 63–75% of years than the yields obtained by applying the recommendations of the research and extension services. From the CDFs curve, there were also significant differences ($P < 0.001$) in yield between application of the recommended N rate (N50) and the farmers' typical application of zero N. Without N application, the farmers' early sowing strategy using a late-maturing cultivar was likely to result in greater yield than using earlier cultivars at later sowings, as recommended by research and extension services, in 60–70% of all years (Fig. 6.2).

Compared to farmers' zero N fertiliser application, the recommended N rate had a significant yield advantage in 85% of the simulated seasons, while the long-term median yields increased by 70–110%. For the normal sowing of a late-maturing cultivar at N50, the yield advantage was greater than the same cultivar when sown late (Fig. 6.3). Compared to the recommended earlier cultivars (medium or early cultivar), the likelihood of yield loss with a late-maturing cultivar increased from <10% to 16% at Melkassa and from <20% to 42% at Adamitulu, as sowing of a late-maturing cultivar was delayed from normal to late sowing (Fig. 6.4). With the application of N50, the late-maturing cultivar yielded appreciably less than the earlier-maturing cultivars in relatively poor seasons and the yield levels were poor (Fig. 6.2). Application of either N25 or N50 did not affect the uncertainty in inter-seasonal yield variability (CV%) compared to N0, when the late-maturing cultivar was selected for the early or normal sowings (Tables 6.4 and 6.5).

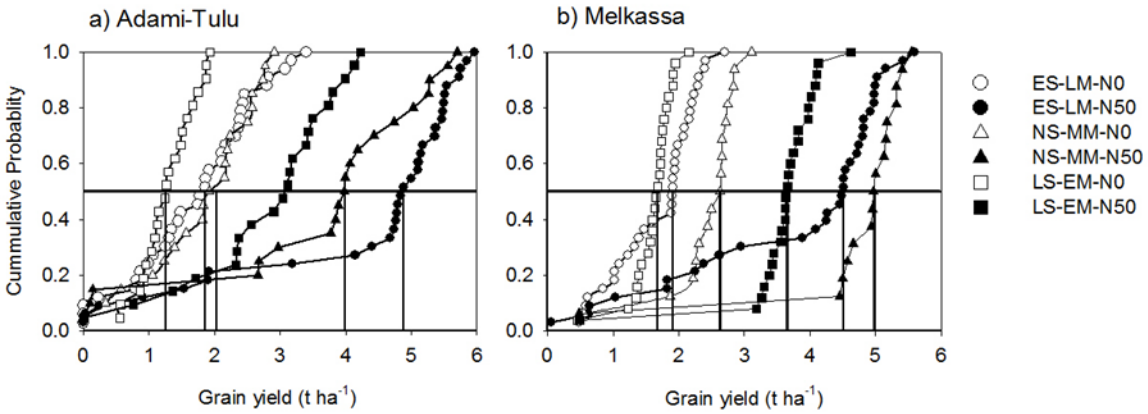


Figure 6.2: Cumulative probability distribution for grain yield based on simulation analysis for early sowing of a late-maturing cultivar at 0 kg N ha-1 (ES-LM-N0) and at 50 kg N ha^{-1} (ES-LM-N50), for the normal sowing of a medium-maturing cultivar at 0 N ha^{-1} (NS-MM-N0) and at 50 kg N ha^{-1} (NS-MM-N50), and for the late sowing of an early-maturing cultivar at 0 kg N ha^{-1} (LS-EM-N0) and 50 kg N ha^{-1} (LS-EM-N50). The intersections between horizontal and vertical lines are for comparing the simulated median yields.

6.3.5. Simulated best management practices

With the application of either N0 or N25, there was a >85% likelihood of a yield advantage from selecting late-maturing cultivars over earlier-maturing cultivars for early and normal sowing windows in Adamitulu, and for all sowing windows at Melkassa (Fig. 6.3 and 6.4).

For the late-maturing cultivar, application of at least N25 could increase the long-term median yields by 44–68% compared to N0, and this increase could be achieved without inducing additional inter-seasonal variability in grain yield (CV = 35–47%) (Tables 6.3 and 6.4). The chance of crop failure at Adamitulu was unlikely when selecting medium-maturing cultivars rather than late-maturing cultivars for late sowing, and the medium-maturing cultivar grown at N25 increased the median yield by 60% compared to N0.

The combination of a late-maturing cultivar grown at N25 increased the chance of exceeding the 'threshold' yields in 75% of all years for the early sowing scenario, in 70–93% of all years for the normal sowing scenario, and in 67–88% of all years for the late sowing scenario. For the late sowing strategy, the chance of achieving the threshold yield using the late-maturing cultivar was equal to that of the medium-maturing cultivar, and this was 15–18% more likely than yields achieved growing the early cultivar.

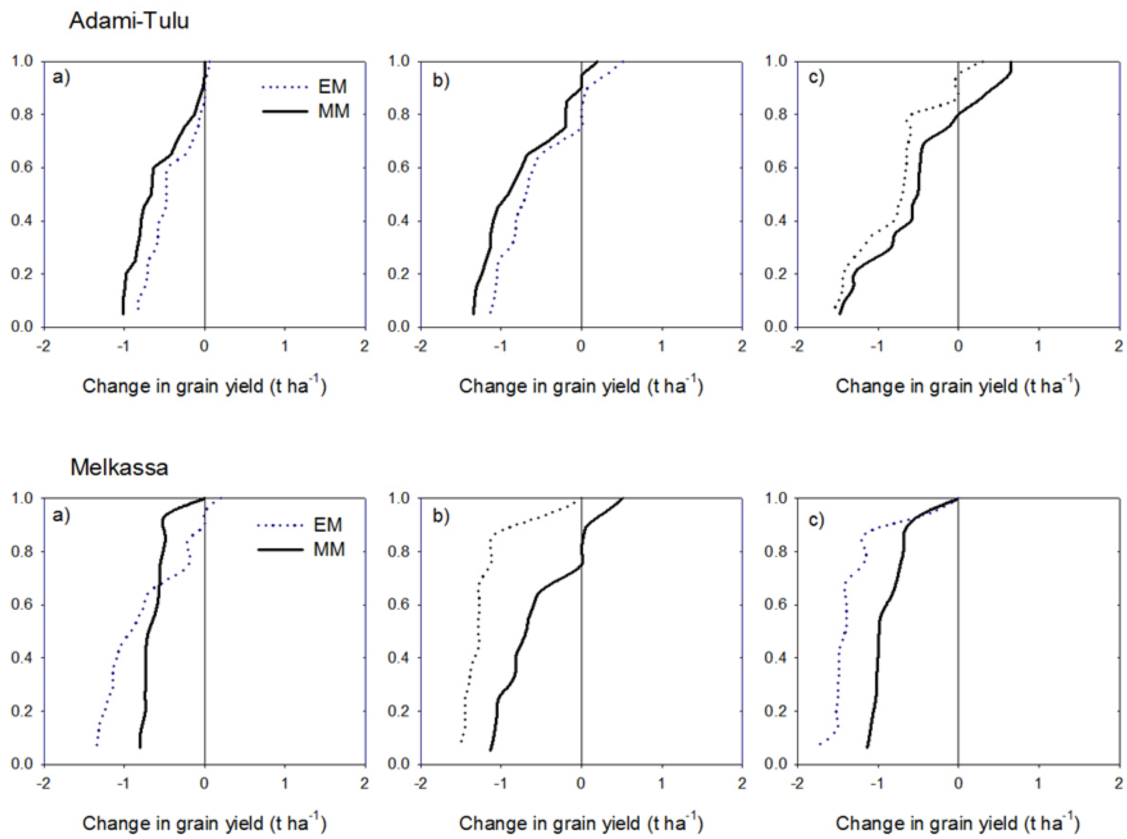


Figure 6.3: Probability of a yield gain or loss for an early- and medium-maturing cultivar relative to a late-maturing cultivar (vertical line) when sown at a normal sowing window (1–15 June) with application of N fertiliser at 0 kg N ha^{-1} (a), at 25 kg N ha^{-1} (b), and at 50 kg N ha^{-1} (c).

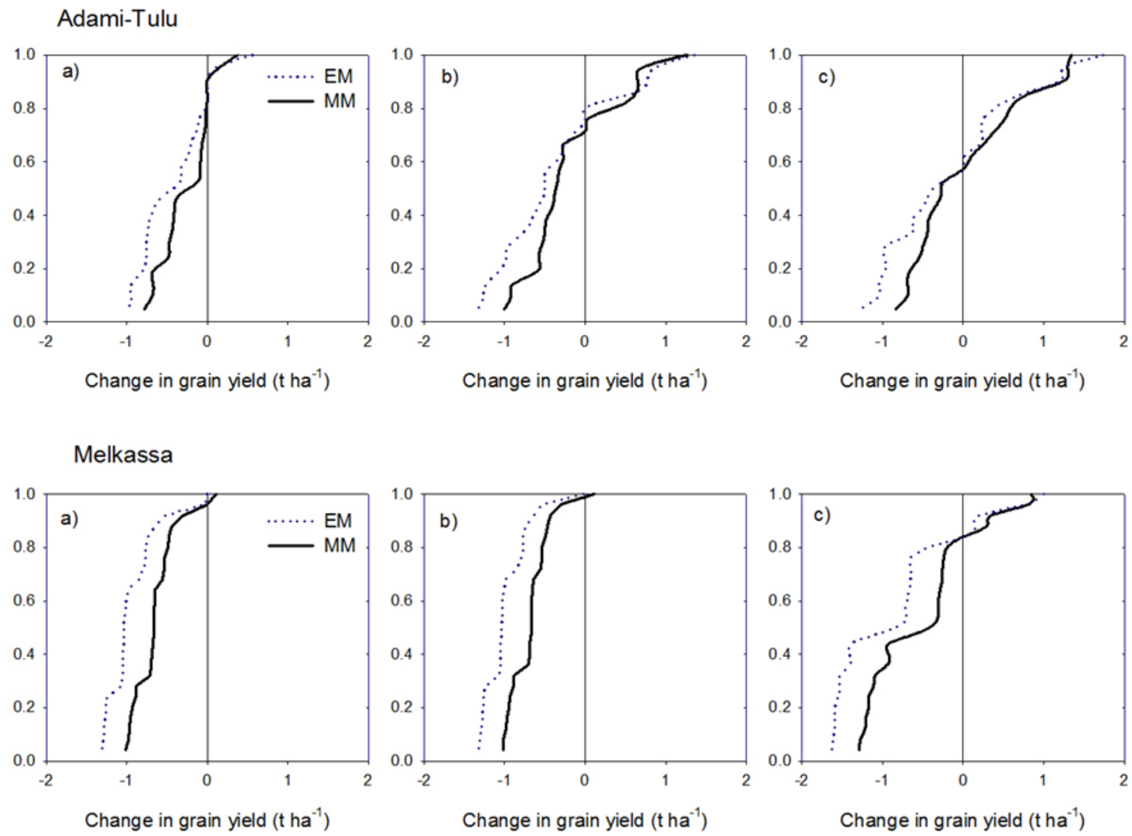


Figure 6.4: Probability of a yield gain or loss for an early- and medium-maturing cultivar relative to a late-maturing cultivar (vertical line) when sown at a late sowing window (16–30 June) with application of N fertiliser at 0 kg N ha^{-1} (a), at 25 kg N ha^{-1} (b), and at 50 kg N ha^{-1} (c).

6.4. Discussion

Characterising the variability of maize grain yields in smallholder systems using crop simulation modelling is not a common research tool in Ethiopia. Previous studies showed that the large yield gap between potential and actual yield was mainly attributed to poor agronomic practices and climate variability (Wang et al., 2012; Meng et al., 2013; Kassie et al., 2014; Getnet et al., 2016). Irregular rainfall, even within the rainy period (Fig. 6.1), has led to management strategies aimed at minimising seasonal risks, rather than maximising production over a longer period (Tables 6.3 and 6.4). There is a need to understand and quantify how weather factors and management practices affect the yield variations of maize for developing better management strategies (Roxburgh and Rodriguez, 2016). For management practices, sowing date, cultivar type, and fertiliser input are the major factors influencing maize yield in the semi-arid region of Ethiopia. During the farmer surveys (Chapter 3), the above-mentioned agronomic strategies were cited by many of the participating farmers as crucial in effectively managing the climate risk that is recurring in the semi-arid CRV of Ethiopia.

Yield reductions due to early or late sowing dates are inevitable depending on the rainfall pattern and maturation characteristics of cultivars (e.g., Sorensen et al., 2000; Kucharik, 2008). Therefore, appropriate sowing dates should be considered with weather factors and cultivar maturation, in order to match crop phenology with the expected water supply (Muchow et al., 1991). The use of crop model simulations could help identify high risk periods for sowing a given cultivar and to analyse the likelihood of attaining higher yields by reducing risk of severe yield reduction, or complete crop failure, due to long dry-spells at any stage of the growth period. As earlier sowing increases the length of the growing season (Kamara et al., 2009; Rurinda et al., 2013) considerable yield advantages could be achieved by selecting a late cultivar, early sowing combination. In production systems where fertilisers are not within farmers' reach, the N flush from the soil early in the growing season is crucial for obtaining high yields (Jagtap and Abamu, 2003). When the rain is not sufficient to ensure an early sowing window, or when farmers are exposed to the risk of crop failure with early sowing, farmers may be forced to re-sow their fields. In this case, farmers would wait for the full onset of the monsoon *kiremt* rain, which is usually in June. Sowing in June at Melkassa could reduce the risk of crop failure while substantially guaranteeing better yields.

At both locations, the simulations indicated that late maturing cultivars tended to out-yield the early and the medium-maturity cultivars when sown at early and normal sowing dates. This suggests that the use of a late-maturing cultivar is a feasible practice in the region for positive yield advantage in most of the simulated years, for achieving considerably greater median yields, and for increasing the likelihood of achieving the threshold yield. For early and normal sowing windows, the late-maturing cultivar did not induce long term risks of crop failure or yield variability for the N rate combinations (Tables 6.3 and 6.4; Fig. 6.2). The model demonstrated that the early-maturing cultivar would not yield any gains for any of the sowing windows. However, for sowing windows later than 30 June, early cultivars (<110 d to mature) would need to be tested as a feasible option for farmers who wish to grow maize after that date. The probabilistic estimates of crop yield showed that farmers would achieve a considerable benefit in the long-term if they opt to select late-maturing cultivars, especially in high to average yielding years. Therefore, research on breeding needs to be tailored towards developing late-maturing genotypes that take >130 days to mature. Unlike Melkassa, medium-maturing cultivars are a better option for risk-averse farmers at Adamitulu where using late-maturing cultivars may risk crop failure or yield penalties in poor, to very poor, seasonal conditions. The correlation between the growth period with the start and length of the rainy season, and rainfall distribution, appears to play an important role in crop yield (Muchow et al., 1991). In general, the late-maturing cultivar can be targeted for both locations when there is early onset of seasonal rain, and the season is expected to be favourable with little risk of crop failure. However, the medium or early cultivar may not have the same yield potential to that of the late cultivar even when they are used in the normal to late sowing window. The reliability of early or medium cultivars with much lower probability of failure should be considered for areas like Adamitulu where the main rain of the *Kiremt* season usually ends earlier than in the Melkassa area. The likelihood of exposure to risk of terminal water deficit at Adamitulu is high. The results from this simulation study also provide impetus for breeding programs to target late-maturing cultivars in their program which may be suitable to the needs of smallholder farmers. If further evaluation in the field confirms that the late cultivars are suitable for normal or late sowing windows, at no additional cost, they have the potential to help farmers improve their productivity by increasing the yield frontier. With the use of crop simulations, crop breeders can easily characterise multi-environment trials into target population of environments (TPE) based on the environmental constraints and the frequency of their occurrence, and impact on phenotype (Chapman et al., 2002). For example, a specific target environment can be defined based on seasonal distribution of drought patterns during the crop cycle (Chenu et al., 2011). Such knowledge of the target environment, can help to predict the likely phenotypic consequences of trait and genetic variation in target environments (Edmeades et al., 2000; Chapman et al., 2003; Chenu et al., 2009; Messina et al., 2009; Chenu et al., 2011).

Crop models can also improve decisions on crop N requirements, and importantly evaluate risk in relation to additional applications of N fertiliser (Hochman et al., 2009). Long term simulations showed that the increasing displacement of the probability curve to the right increased in response to application of N50 as the seasons' productivity level increased (Fig. 6.2). For example, farmers could achieve maximum yields of 5.8–6 t ha^{-1} when a late cultivar was supplied with N50. However, fertiliser recommendations for subsistence maize farming systems should be geared towards yield stability and achievement of a threshold yield in any given year (Akponikpè et al., 2010; Kisaka et al., 2015). Irrespective of cultivar type, simulations showed that seasonal yield variability increased significantly with an increase in N rate applied as indicated by CV% values for early sowing. As sowing was delayed to normal- and late-sowing windows, temporal variability in grain yields with N fertiliser application decreased while the long-term median yield increased. For example, applying N fertiliser to the late sown maize reduced seasonal variability in grain yield at Melkassa, regardless of the cultivar choice. This suggests a less level of variance in year-to-year grain production was established at Melkassa by application of N fertiliser to the late sown cultivar (with fertiliser application, CV of 48% was reduced to 38%) over the simulation period. Differences in yield responses to inorganic N fertiliser between the different management systems (sowing time and cultivar type) may provide a basis to discourage farmers to adopt the current "blanket" fertiliser recommendations.

The effect of seasonal rain varying in amount and distribution is one of the determining factors in affecting the temporal water supply to the maize crop (Muchow et al., 1994). This rainfall-related factor often imposes a risk in achieving better responses to N fertiliser, and many farmers do not like the risk associated with the use of expensive fertiliser in low and unpredictable rainfall environments (Dimes et al., 2011). There were some years that the modelling showed no grain yield at the study area. Similarly, total failure of a crop due to water stress was reported, even with the application of N fertiliser in semi-arid environments (Barron et al., 2003; Kamanga et al., 2014), However, the large yield responses to N applications in more than 90% of the seasons (Tables 6.3 and 6.4) suggest that an investment in N fertiliser by the farmers would be a relatively low risk option for farmers when maize was sown during the *Kiremt* season. And yet, 78% of farmers do not make this investment (see Chapter 3). The possible reasons for this are many: poor extension service or service advice, low technical efficiency due to blanket application to vastly diverse environments, lack of money to buy fertilisers, lack of economic incentives to apply fertilisers or lack of confidence in higher economic returns due to drought, untimely availability of inputs and/or weak markets, and/or lack of knowledge about beneficial effects of fertiliser use on the soil resource (Rötter and Van Keulen, 1997; Morris et al., 2007; Spielman et al., 2010). Enhancing social capital for promoting informal credit exchange among farmers, improving farmers' financial capacity to buy fertilisers, and encouraging private fertiliser markets are key factors for alleviating the problem of poor inorganic fertiliser use in Africa (Knack and Keefer, 1997).

The model scenario at the study locations has shown that the use of moderate rates of N fertiliser may give greater yield responses with lower risks of crop failure. Farmers, who are faced with intermittent financial problems, should consider a low-cost application that would guarantee the minimum threshold maize yield even during a poor season (Jagtap and Abamu, 2003; MacCarthy et al., 2009; Kisaka et al., 2015). The application of 25 kg N ha^{-1} seems more acceptable as it guarantees a higher minimum yield in poor years and low inter-seasonal yield variation, thereby reducing exposure of smallholder farmers to climate risk. In addition to the high nutrient efficiency of micro-dosing technology, due to the targeted application of small rates of N fertiliser even under quite dry conditions, the technology is promising for its cost-effectiveness which may result in economically viable productivity gains for resource-poor farmers in SSA (Dimes et al., 2002; Twomlow et al., 2010). Many farmers will be more likely to adopt this technology as long as it is appropriately demonstrated in SSA (Twomlow et al., 2010, 2011). As farmers see a positive response, they would be encouraged to make further investments in fertiliser. However, farmers need to be advised to employ good management practices (i.e., timely sowing, cultivar choice), that directly influence crop yields to realise the potential yield increases due to the application of N fertiliser (Tittonell and Giller, 2013; Kassie et al., 2014; Getnet et al., 2016). Once farmers start to witness the yield gain from application of modest rates of N fertiliser, they may be convinced that future yields from application of high rates of N fertiliser can be maximised in favourable seasons enabling farmers to store the extra grain harvest as a buffer against poor or drought years (Rurinda et al., 2013).

As some farmers indicated during the farmer surveys (Chapter 3), a lack of response to inorganic fertiliser have been reported in other areas with low yields, particularly in situations where soil carbon levels have fallen to below 0.5% (Nziguheba et al., 2010). Many farming systems are reliant on nutrient mining with consequent declines in soil fertility and higher production risks in the long term (Snapp et al., 1998; Ncube et al., 2007; Vanlauwe et al., 2011). In the study area, there is no return of crop residue into their soil because stover production is low and there are competing uses for stover, and soil degradation due to continuous loss of soil organic carbon is expected. In such instances, nutrient use efficiency is low unless the poor soil organic carbon stock of the soil is restored (Zingore et al., 2007a and b). The promotion of the use of smaller doses of fertiliser without residues in Africa can be based on a number of logical arguments (Dimes et al., 2015). For example, when farmers apply crop residues in the N-poor cropping systems, there is a need to adjust fertilisation to compensate soil N immobilised in the short term, which can result in lower N-use efficiency compared with conventional systems. Recent research has highlighted the possibility of organic fertilisers in restoring carbon inputs to the soil, but more realistically a substantial increase in use of inorganic fertiliser is also urgently needed to boost soil organic carbon (SOC) through added biomass (Tittonellet al., 2008; Chivenge et al., 2011). McCown and Jones (1992) claimed that smallholder farmers would remain in a 'poverty trap' unless the continual loss of SOC is positively shifted towards a consistent improvement in SOC of the soil. In general, N-use efficiency of the crop could be improved if the spatial heterogeneity of smallholder farms is considered, and more effective fertiliser recommendations are designed for targeting existing soil fertility niches (Tittonell et al., 2007b). In an environment with poor soil quality, eco-efficient intensification of crop production can be ensured by demonstrating to farmers the benefit of applying mineral fertiliser and residue retention practices for renovating and building up the SOC stock (Fischer et al., 2014).

Based on data collected from three sites in the CRV of Ethiopia over 6–12 years, the gap for rain-fed (non-irrigated) maize yields obtained by smallholder farmers compared to yields from well-managed on-farm fields is in the order of 55 to 129% (Kassie et al., 2014). There is potential for narrowing the gap between the yields achieved in smallholder farms and those that can be achieved through improved management practices (Kassie et al., 2014). Given that smallholder systems are often low input, especially in SSA, there is likely much to gain from encouraging farmers to improve their technical efficiency gains from applying better agronomic management thereby extracting the full return from current technologies such as investment in N fertiliser input (Keating et al., 1991; Tittonell et al., 2008). In general, change in agronomic management and input investment strategies are needed in reducing risk associated with climate variability while improving production levels. Addressing farmers' perception and management of the added risks from such changes in practice is a critical endeavour for successfully improving the eco-efficiency frontier (Carberry et al., 2013). Resources would be used more efficiently if maize grown on smaller, well-managed field and inorganic fertiliser applied at moderate rates rather than cultivating large portion of the fields and without applying inorganic fertiliser at all. As farmers is ensuring increase in the productivity of their staple maize crop for satisfying their household food demand, they are able to set aside land for the production of high value cash/market crops.

APSIM predicted the seasons when crop failure and low yield levels occurred and this matched what farmers said when they were interviewed. APSIM was effective in providing information about the risk of seasonal weather to maize production in this region. By complementing APSIM with field trials, cropping practices that are practicable, low-risk, and adoptable can be developed for the wide variety of soil types and climatic conditions in the region. For the simulation study, only the parameterised soil data and single condition for the initial soil parameters were used as baseline information for model application. However, it would be necessary to represent the various typical site-soil conditions (soil fertility, PAWC, and plant rooting potential) of the study region to study the drivers of yield responses to fertiliser N as influenced by a range of management scenarios and site-specific conditions of the study region.

Adoption of a technology by farmers is not mainly based on its agronomic performance but by other factors/uses that would be important to the overall farm production and household needs (Becker et al., 1995). These are dictated by production, economic, resource-use efficiency and environmental measures. Integrative assessments of whole farm systems that combine crop yield changes with socio-economic-value chain scenarios (Power et al., 2011; Rodriguez et al., 2014) can be done using simulation modelling in combination with agent based models (ABM) within a participatory action research approach (Meinke et al., 2001; Carberry et al., 2002; Castella et al., 2005; Valbuena et al., 2010). As a result, farmers, researchers and scientist can be engaged in a co-learning process so that important information can be generated that would help the key actors, including farmers, envisage all available alternatives on what they can achieve for their farms. This would help determine 'best fit' technologies that could be best combined at the farm level to maximise productivity while reducing production risks of the farming system in variable and uncertain climates (Carberry et al., 2002; McCown and Parton, 2006; McCown et al., 2009; Dimes et al., 2015).

6.5. Conclusion

In the semi-arid CRV of Ethiopia, farmers make decisions on cropping patterns as well as agronomic management strategies that include sowing time, cultivar type, investment into fertiliser input, and so on. Crop simulation and modelling approach can play an important role in research and development endeavours to identify strategies which are tailored to the variable season climate conditions of the semi-arid region. For the yield simulations using early sowing dates before June, there were better sowing opportunities than normal or late sowing windows, however, the probability of crop failure was very high. This is consistent with the experiences of the smallholder farmers at the study area who reported that there is high risk of yield loss in the early sowing window. The model simulation output also showed that farmers could tap into yield gains from the late-maturing maize cultivar, if farmers give up a sowing opportunity before June and wait until the normal and late sowing window for Adamitulu and Melkassa, respectively. The simulated probability distribution of yield for 0 kg N $ha^{-1}$is very steep, and it is indicative of a less variable, low productivity and low risk cropping system. Relative to the farmer baseline application of 0 kg N ha^{-1}, the locally recommended rate of 50 kg N ha^{-1} can be expected to have negative effects on yield in about 10–20% of the seasons, whereas maize yields of over 3 t $ha^{-1}$are achievable in favourable seasons with a likelihood of occurring in 50% of the seasons. The findings suggest that the resource-poor farmers of the study areas, who traditionally grow maize without application of N fertiliser, need to be educated about the benefit of investing in modest amounts of fertiliser, as a feasible pathway for sustainable intensification of the maize systems in the CRV region. In general, the inter-seasonal variation in maize yields due to high rainfall fluctuations at both a temporal and spatial scale indicates that a blanket recommendation of N fertiliser as 50 kg N ha^{-1} for maximum grain yield cannot easily be transposed among the diverse locations in the region. The retrospective analysis using probabilistic estimates of maize yield for the historical weather data can be an effective means to assess the likely production risk as a consequence of various sowing opportunities along with different cultivars of varying maturity type and different rates of N fertiliser. Linking the capability of a bio-physical model with participatory research can be more effective for delivering effective management strategies that can fit into the bio-physical and socio-economic conditions of the smallholder farming systems in the dry land areas of Ethiopia.

Chapter 7 General discussion

7.1. Summary of the thesis

A systems approach was employed to assess the bio-physical components of the farm as well as farmer activities in an attempt to solve complex problems in farm management. A systems approach is a novel method to capture the key bio-physical components of the farming system as well as the subjective perceptions, values and preferences of the smallholder farmers in risk-prone environments. The conventional approach of agricultural research and development is inadequate as it is poorly equipped to address the more complex situations of heterogeneous smallholder farms in climatically variable regions where multiple social, economic, and perceptual factors influence decisions and practices (Darnhofer et al., 2010). As a result, many of the promoted technologies and production strategies from conventional agriculture research and extension services have not been adopted by a number of smallholder farmers, partly because the promoted 'solutions' did not address their needs or particular situations (Brossier and Hubert, 2000). Systems approaches enable the incorporation of multiple perspectives in the analysis in order to understand the complex, variable and dynamic nature of the farming system and the processes through which beneficial changes can occur (Reynolds and Holwell, 2010). Depending on the type of problem(s) to be studied in the agronomic system, various systems-based research outcomes can be employed to address the issues raised at a specific scale (Kropff et al., 2001). Therefore, a thorough understanding of a system, at a field or farm scale, in the context of risk and uncertainty under variable climatic conditions is a requisite in order to capture the highly variable environment and production system, along with the multiple characteristics of smallholder farmers regarding their production objectives, aspirations and preferences. Such systems analysis can therefore assist in targeting locally relevant and effective management interventions that are in tune with the current, and increasingly variable future climate conditions, helping to achieve more sustainable, resilient and economical smallholder farming systems.

The choices of farmers are not based on 'objective' facts, but influenced by many other factors such as their perceptions, risk attitude, resource level as well as by their values and by the activities of other members of the rural community. Various participatory approaches can be applied to account for the local farmers' views and perspectives within a systems analysis framework (Lynam et al., 2007). In this study, Rapid Rural Appraisal (RRA) were used as a quick and efficient method to conduct a diagnostic survey at Bosset and Adamitulu Jido-Kombolcha districts in the semi-arid region of the CRV in which farmers were engaged in a participatory fashion through individual interviews as well as focus group discussions (FGDs). In the region, variability in crop yields are directly tied to the rainfall in a given year, and as a result, there is a high uncertainty in crop production (Adimassu et al., 2012). The RRAs method allowed better insights of the complexity of how smallholder farmers perceive climate from one season to the other, and how the perceived and anticipated seasonal climate affects their cropping systems in terms of productivity and risks. In addition, a better understanding was gained regarding how farmers' perceptions and knowledge of their local climate affects key agronomic decisions in response to the varying climate, particularly varying seasonal rainfall patterns. Therefore, the study was designed to be valuable for researchers and extension advisors in tailoring their services to suit farmers' needs and support them in strengthening their capacity to better manage climate induced risk and uncertainty (Moyo et al., 2012; Rao et al., 2011; Campos et al., 2014).

In the study districts, farmers were able to recollect historical climate patterns fairly accurately, and their responses did coincide quite well with that of the historical observation of rainfall events at each study location. In general, farmers' collective perceptions of, and criteria to describe various seasonal climatic conditions, are based on a combination of various factors that affect crop production and are not entirely based on climatic observations. According to farmers, the way a given seasonal rainfall (timing of the seasonal rains and within-season distribution of rain) affects their crop at critical stages of growth and its final productivity is deemed the major determining factor to define a given seasonal climate as being 'good', 'average' or 'bad'. Across individual, as well as different groups of farmers at each study location, there was a good deal of unanimity regarding their perceptions of varying seasonal climate scenarios, as well as their ratings of the local season-type, which corroborated fairly well with local meteorological records at each location. However, the study has also highlighted the general tendency of farmers to underestimate the good seasons. Similarly, many researchers have reported distortions of famers' probabilistic estimation of good and bad seasons of their local environment affected by high inter- and intra-seasonal climate variability and risk (Sherrick et al., 2000; Rao et al., 2011; Moyo et al., 2012) due to the psychological tendency of humans to pay more attention to, and give more weight to, negative impacts that are often attributed to a phenomenon known as ‘negativity bias’ (Hansen et al., 2004). The apparent similarities amongst individual farmers and between groups of farmers in how they perceive climate variability may be due to deeply ingrained beliefs and attitudes. Nevertheless, discrepancy between farmer perceptions and scientific observations might often be the case. In one way, meteorological definitions of rainfall anomalies do not consider the seasonal rainfall supply in relation to crop demand (Wilhite and Glantz, 1985; Osbahr et al., 2011) which is an important parameter that many farmers consider to describe their local climate. On the other hand, it is questionable whether this mismatch is due to inadequacy of the analytical method to capture and measure the real experiences farmers use to form their perceptions, or whether it is due to the subjectivity and biases in farmer observations and understanding (Coe and Stern, 2011; Rao et al., 2011).

In general, farmers responded to the variable climate by modifying their agronomic decisions according to the actual, perceived and expected seasonal rainfall pattern. However, most key decisions are actually made at sowing and include agronomic decisions such as what crop species to sow, careful choice of cultivars and the portion of land being allocated to different crops and whether they should apply inorganic fertiliser. Moreover, farmers diversify their cropping practices using a mix of crop species both in space and time. Many of the interviewed farmers altered agronomic decisions in response to the seasonal rainfall pattern to better manage their exposure to climate variability (Pandey and Bhandari, 2009), however, agronomists simply recommended a fixed sowing window when rains were assumed to be reliably established in June when the main season rain, *Kiremt*, settled in. However, the effect of varying sowing dates and different cultivars on maize (*Zea mays* L.) yields, has yet to be properly evaluated in the semi-arid region of the CRV. As much effort in breeding research for semi-arid agro-ecologies is directed towards development of early- to medium-maturing cultivars instead of drought tolerant, late-maturing cultivars, many of the locally released cultivars have a crop maturity adapted to the length of the *Kiremt* season (i.e., June–September) (Mohammed and Mulatu, 1993; Bogale et al., 2011). However, many farmers in the CRV aim to maximise grain and biomass yield by sowing late-maturing maize cultivars, especially if early rain in the *Belg* season (March/April–May) occurs.

In the CRV of Ethiopia, soil nitrogen(N) is the most limiting nutrient in crop production (Adimassu et al., 2012), Soil fertility is generally degraded due to the ongoing nutrient mining associated with continuous cropping combined with limited use of fertiliser in any form (Biazin and Stroosnijder, 2012). However, more than one-third of all participating farmers in the study area of the CRV believe that their fields are fertile or unresponsive to inorganic fertiliser input. Significant numbers of farmers in the CRV do not apply fertiliser because they think it offers no gain in crop yield, nonetheless, this hardly means that farmers are wrong regarding their perceptions of fertiliser use to increase their crop yield. In support of this perception, Getnet et al. (2016) reported that marginal differences have been observed between fertilised and unfertilised on-farm fields across many sites within the CRV region. Given the poor fertility status of most soils in the CRV region due to low soil organic matter, lower than expected, or no responses to fertiliser is expected (Zingore et al., 2007a and b; Marenya and Barrett, 2009; Nziguheba et al., 2010). However, much emphasis has been placed on the stimulating use of fertilisers without critically examining where fertiliser is efficient and where it is not (Sileshi et al., 2010). Further studies may be required to verify whether the soil organic stock of these fields is really so degraded and poorly responsive. If this is confirmed, intervention through integrated fertility management using organic fertilisers must be a priority to restore carbon levels in the soil, however, a substantial increase in the use of inorganic fertiliser is required to boost soil carbon through added biomass from crop residue, or the inclusion of a robust N-fixing legume species in efforts to reduce yield risks and increase adoption by smallholder farmers. As a result, degraded soil can be restored and crop yields increased (Tittonell et al., 2008; Sileshi et al., 2010; Chivenge et al., 2011).

Like many smallholder farmers in the semi-arid region of Africa, many farmers in the CRV Ethiopia perceive there is higher risk of cash investment in high-priced fertiliser, and their risk-averse behaviour may act as a major deterrent in using inputs and taking advantage of improved technologies (Dimes et al., 2011, 2015; Twomlow et al., 2010). Recommended technologies should therefore include adequate information about probabilistic estimates of expected benefit and risk associated with the proposed technology under variable climates (Gadgil and Rao, 2000), so smallholder farmers can make informed decisions depending on their risk preferences and resource limitations (Rao et al., 2011). Thus there is a need for researchers to work in close collaboration with local extension officers in order to develop site-specific and climatically-relevant agronomic management strategies that can effectively adapt according to the local soil fertility status and the risk of input investment (Twomlow et al., 2010; Roxburgh and Rodriguez, 2016).

In general, farmers use incomplete or imperfect knowledge to make technical and financial decisions under complex, variable and dynamic farming systems (Rodriguez and Sadras, 2011). Running field experiments for exploring the complexity of interactions of the bio-physical and management components within a farming system are often too expensive or require long study periods to produce results representative of the system under study (Donatelli and Confalonieri, 2011). As a result, it is difficult to clearly unravel such information based on only a few years of field-based experimentation in a context of risk and uncertainty associated with climate variability. Alternatively, computer simulation models can be used as effective and efficient tools for analysing a system under investigation as well as estimating system performance based on crop-soil interactions under the driving forces of climate and management impositions (Donatelli and Confalonieri, 2011). In particular, relevant and credible crop simulation models can assist in providing answers to various research questions through exploring management scenarios in the context of historical long-term climate variability (Meinke et al., 2001; McCown et al., 2009). In a systems approach, simulation modelling offers the possibility to better understand the various complex bio-physical processes and their non-linear interactions when crops are grown under varying environmental and management factors. Identifying best combinations of genetic resources (G) and management practices (M) adapted to target environments (E) is, however, limited by the ability to identify favourable combinations of G, M and E given the resources available to explore among the myriad of possible combinations (Messina et al., 2009; Hammer et al., 2016). Crop simulation models like the Agricultural Production Systems sIMulator (APSIM) have been successfully applied in modelling smallholder farming systems in Africa (Whitbread et al., 2010) and are effective in capturing the interaction among different production system, soil, climate, and management factors (G x E x M) (Hammer et al., 2014; Holzworth et al., 2014).

For effective application of crop models like APSIM in Ethiopia, however, data availability is typically a major limitation. In this study, a comprehensive data set was generated for modelling rain-fed maize systems in the CRV of Ethiopia. The dataset cover historic daily weather records and location-specific data related to crop growth and productivity, along with soil parameters to represent key system processes in both the crop and soil arena. After APSIM parameterisation, the model was found to be robust in reproducing the various system processes, as evidenced by the good agreement observed between the simulated and the corresponding observed values of crop phenology, grain and biomass yield and stover and grain N concentrations as well as soil water dynamics. This was demonstrated in a statistically robust manner in which the model simulated the observed behaviour within the bounds of experimental uncertainty. For the study, a standardised collection of the most important bio-physical data (climate, soil and crop) was prepared to generate the essential input parameters for future model use in the semi-arid region of Ethiopia. For evaluating APSIM, datasets of six seasons from replicated field-based experiments at Melkassa were used to evaluate responses of the locally-adapted medium-maturing maize cultivar (cv. *Melkassa-2*) to differing sowing times and rates of N fertiliser. The various datasets were subsequently used to evaluate key aspects of model performance at varying seasonal growth conditions with a range of seasonal rainfall patterns, soil water and N regimes. The veracity of the locally-parameterised APSIM model in simulating crop phenology, above-ground biomass and grain yield was quite acceptable across the diverse dataset at the study location, and its performance must be considered adequate over the diverse dataset across a range of seasonal climates and imposed management practices. Furthermore, the model was tested to observe if it was capable of capturing variability in maize yields of five participating farms near the Melkassa area. The farmers were selected during the RRAs and recorded their detailed farm activities over two years (2010–2011). Yield distributions from farmer surveys and model outputs were compared to evaluate the performance of the model, and it was realistic in simulating maize yield as a consequence of local management practices imposed by the case study farmers. Therefore, the model was found robust and credible to be used for long-term simulations for *in-silico* experiments in evaluating the effect of various combinations of key agronomic management scenarios (i.e., sowing date, cultivar type and N fertiliser strategies) on production levels and risks of the maize-based cropping system in the region.

Simulation and modelling is therefore a powerful approach for assessing technical feasibility and system performance for a crop production enterprise. For example, a crop model can be applied to evaluate performance of a maize system by exploring opportunities and risks associated with the various key management strategies, and *ex-ante* evaluation of the various simulation scenarios in the context of long-term climate variability. For the study, a modelling approach was applied as a means to enhance strategic learning as well as to identify feasible and flexible management options as possible future recommendations that can be adapted according to perceptions, risk preferences and resource levels of smallholder farmers who are operating in environment affected by climate risk. Learning about the effects of climate variability on crop yield using simulation modelling can therefore replace researchers', farmers' and their extension advisors' intuitive understanding with expectations of likelihoods derived from quantitative analyses (McCown et al., 2012), and therefore help to quantify the risks of various management options in the context of long-term climate variability (Meinke et al., 2001; McCown et al., 2009).

In general, it is evident that the semi-arid regions of CRV Ethiopia in which systems are reliant on rainfall as a sole source of moisture for crop production, seasonal rainfall variability inevitably leads to highly variable production levels and risks. As a consequence, there is a growing need for increasing crop yield whilst reducing inter-seasonal variability or uncertainty in crop production. As a result, smallholder farmers' livelihood as well as food security at a household level can be improved in the study region. Developing effective agronomic strategies, such as best-fit combinations of agronomic components, including sowing time, cultivar choice, and affordable investment in N fertiliser could be a stepping-stone approach for sustainable intensification of smallholder crop production systems. Therefore, crop simulation is a quick and cost-effective way of exploring "what if" scenarios and formulating alternative management strategies that are effective for a specific location and farmer situation. This approach can assist farmers and their extension advisors in making informed decisions in the context of risk and uncertainty associated with climate variability. Among the various management decisions, farmers identified sowing time, cultivar choice and N fertiliser as the most important management factors they would consider, so they adjust their decisions based on these agronomic components according to the perceived or anticipated seasonal rainfall pattern at their specific locality. Therefore, APSIM was then configured to run long-term simulations of alternative management options including farmers' key management scenarios, as identified by the participating farmers as important during the farmer surveys (RRAs), along with those recommended by agronomist/extension services. In the study, APSIM was also used to quantify production risks and yield benefit, or opportunities of yield gain, as a consequence of various combinations of agronomic management factors under varying climates (Whitbread et al. 2010, Carberry et al. 2004). Such estimates can be expressed as probability distributions, which allow quantification of production risks and levels in the context of long-term climate variability in a given locality. Therefore, a scientific study using a valuable tool such as APSIM, can play a key role in reducing farmers' uncertainty about the outcome of various agronomic strategies and decisions by applying their local practices and existing standard practices from extension services, along with adopting new innovative practices under varying climate, soil water and N supply conditions (Bouma and Jones, 2001). This approach can, therefore, allow researchers to provide farmers and their extension advisors with timely and relevant advice to help shape their local farming practices and significantly improve the capacity of smallholder farmers to better adapt locally relevant agronomic and technological strategies in the face of existing and evolving risk associated with climate variability.

In general, maize productivity in the study area will be limited without fertiliser input regardless of sowing time and cultivar type. Multiple-season scenario analysis of the maize system revealed that moderate application of 25 kg N ha^{-1} can improve both the long-term median and the minimum threshold yields of maize while reducing yield variance across the seasonal conditions. Whilst greater gain in productivity was possible with 50 kg N ha^{-1}, it is at the expense of increasing inter-seasonal variability in yield. An important implication is that making a uniform recommendation (e.g., ‘blanket’ application of fertiliser) based on performance under mean conditions may not be appropriate in environments where climate variability results in high seasonal fluctuations in crop production. Unsuitability of blanket application rates of fertiliser for the traditional ‘representative farmer’ is considered to be a key barrier to uptake of fertiliser use in the smallholder farming systems (Snapp et al., 2003; Whitbread et al., 2010). Therefore, smaller doses of fertiliser will be more acceptable as a first step in creating interest among resource-poor farmers in the region, who are reluctant to use inorganic fertiliser (Dimes et al., 2015). It has been demonstrated by Rao et al., (2011), that farmers at the study area greatly over-estimate the downside to yield risk and this plays a role in discouraging investments such as N fertiliser in their crop production (Cooper et al., 2008).

For this study, the parameterised local soil of Melkassa was assumed to be representative of good cropping soils in each of the study locations. The simulation of yield responses to N fertiliser as influenced by a range of agronomic factors, local climates and soil conditions (soil fertility, plant available water content and plant rooting potential) is considered to be a robust method for analysing various agronomic factors as the key drivers of N response across diverse locations in the CRV region. Given the soils in many parts of the semi-arid region are generally poor, investment in inorganic fertiliser are required to sustainably increase both crop and farm productivity. The scenario analyses also highlighted the limitation of N as a major constraint in the study system, and the importance of N fertiliser for sustainably enhancing maize productivity. However, many of the interviewed farmers are concerned about perceived and realised seasonal risks associated with investment in N fertiliser. Irregularity of rainfall, even within the rainy period, has led farmers to a strategy of minimising seasonal risks, rather than to one of maximising production over a longer period (Schouwenars, 1988). Application of N fertiliser at a recommended rate of 41–64 kg ha^{-1} has been a standard practice in the study region (Debelle et al., 2011; Kassie et al., 2014), however, the vast majority of smallholder farmers have not adopted this recommendation because of its cost and the greater exposure to risk associated with the higher levels of investment (Getnet et al., 2016).

The APSIM model also demonstrated that farmers can reduce risk and increase productivity of their maize system by adapting the most effective management measures such as sowing of a late-maturing cultivar at Adamitulu, either in the *Belg* season between March and April, or in the *Kiremt* season when monsoon rain settles in between early to mid-June. In places like Melkassa, farmers would be better off if sowing is postponed to June in the *Kiremt* season. The grain yield response of the late-maturing cultivar grown with application of 25 kg N ha^{-1} was equal to that of the medium- and the early-maturing cultivars grown with 50 kg N ha^{-1}, when compared in the early sowing scenario at Adamitulu and in the normal and late sowings at Melkassa. However, additional analyses with differing N application strategies than those used here are required to provide guidance on ways that may improve both N use efficiency and economic returns for N fertiliser use as expressed in the form of probabilistic estimates.

Irrespective of sowing time, farmers could achieve greater yield gain and less risk of crop failure with a late-maturing cultivar than the recommended early or medium cultivars, except for late sowing at Adamitulu where there was high risk of crop failure in ~15% of the simulated years. This finding is consistent with the experience reported by the farmers. In contrast a late sowing opportunity with a late-maturing cultivar may not be an option in some places like Adamitulu, and must be managed differently from earlier maturing cultivars to avoid the possibility of producing crops with high biomass which are unable to fill grain due to water stress at the end of the season. Early maturity is also an important trait in areas where the season is short and terminal drought is common (Barnabás et al., 2008; Lopes et al., 2011). At a location like Adamitulu, farmers could avoid the risk of zero yields by selecting an early- to medium-maturing cultivar for a late sowing opportunity. By following these strategies, maize responses to fertiliser inputs could be substantially maximised without increasing the risk of crop failure or inter-seasonal variation of yield. In general, using late cultivars for early to normal sowing opportunities could raise maize productivity under smallholder farming systems; however, this requires further evaluation in the field. The results from this simulation study may also provide additional impetus for breeding strategies to target late maturing and drought-tolerant cultivars in their research program. This may help avoid situations where farmers' knowledge gaps in simple principles of good agronomic practices such as suitable cultivars and sowing dates, lead to large yield gaps (Roxburgh and Rodriguez, 2016). According to Dimes et al. (2015), simple agronomic management can lift yields and reduce yield variability and risk for approximately 30–40% of farms across eastern and southern Africa. In conclusion, basic agronomic management that accounts for the specificities of local climate and soil conditions can help farmers improve their productivity by increasing the yield frontier at no additional investment cost (Roxburgh and Rodriguez, 2016). For the study area, desirable agronomic management practices in combination with modest rates of N fertiliser can significantly increase maize yield without additional risk. Similarly, fertiliser use, even at small quantities, seems to offer further gain in crop yields in semi-arid Africa (Twomlow et al., 2010; 2011), and this is particularly the case when fertiliser use is linked with better cultivar and agronomic management strategies, in part, due to their greater responsiveness to this input (Roxburgh and Rodriguez, 2016).

This study demonstrates how simulations can help identify agronomic management strategies that may still lead to increase in yield gains in the face of climate variability with minimum fluctuations in crop production and risk of crop failure. Therefore, farmers in the CRV of Ethiopia have an opportunity for a significant increase in maize production by improving their technical efficiency through better management and increasing the use of fertiliser input. In particular, if context relevant information on climate related risk and returns is provided to farmers in the semi-arid environment, they might feel more confident to invest in crop production and technologies. This may be considered as a stepping-stone in the dissemination of knowledge- and cash- intensive technological innovations (e.g., high application of fertiliser, CA and ISFM) that promote the inclusion of both agronomic and natural resources management practices as critical elements of a balanced and sustainable agricultural intensification package. The flow–on effects are expected to provide benefits to smallholder farmers by sustaining their yields in the long term (Giller et al., 2011a; Shiferaw et al., 2014; Dimes et al., 2015; Roxburgh and Rodriguez, 2016).

7.2. Methodological limitations of the study, conclusion and the way forward

As variability in season rainfall pattern is the main cause of yield variability and production uncertainty in the region, this study demonstrated the potential of crop simulation and modelling as a new research tool in Ethiopia to determine the magnitude of inter-annual maize yield variability and risk of crop failure associated with current and alternative innovative management strategies in the face of climate variability(Keating et al., 2000; Hansen, 2005; Moeller et al., 2008; Meza and Silva, 2009; Rodriguez et al., 2014). Moreover, the use of crop models can offer leverage for researchers to identify potential agronomic and fertility management opportunities that can increase crop yield while reducing production risk for smallholder farmers according to their risk preference and resource level. As a result, it could provide a clear picture to farmers or farmer groups about the risk dimension of the various management scenarios. The issue of whether the various adaptation strategies for current climate variability are also effective to climate change remains to be resolved (Hochman et al., 2017b). Anyway, this can provide a benchmark of yield variability against which future climate change induced variability may be compared. However, farmers' capability to better adapt to the challenge of current climate variability must first be enhanced, otherwise the challenge of adapting to future climate change with anticipated increases in climate variability will prove daunting for most, and impossible for many (Cooper et al., 2008).

In a context of risk and uncertainty associated with climate variability, farmers could only make better decisions from the long-term simulation scenarios if the risk information associated with existing and innovative practices can be properly discussed with and communicated to farmers. In conclusion, the use of crop models with long runs of daily climatic data provide a quick and less costly opportunity to create a 'virtual world' wherein simulation experiments may be conducted in concert with farmers to facilitate a co-learning process and practical management decision-making, leading to the development of more productive, profitable and resilient farm businesses (Rodriguez et al., 2011). The model, however, needs to be rigorously parameterised and well tested for representative locally-adapted crop cultivars of varying maturity-type, along with a range of production systems, key management impositions and environmental factors (i.e., dominant soils and local climates). This may allow for the model to be used to its full potential as well as warranting researcher confidence in using such a model as a state of the art tool for cropping systems research to simulate new and innovative practices across a greater array of environmental conditions. Moreover, the scenario outputs of APSIM from the long-term simulations and modelling can be effectively applied to support local farmers and their extension advisors in making informed decisions through adopting locally relevant and desirable management strategies and practices. Multiple management options can be applied in targeting feasible interventions according to specific bio-physical and socio-economic conditions that can therefore improve resource-use efficiency under the prevailing climate risk and N-deprived system whilst enhancing production levels and risks of the maize-based cropping system.

Systems approaches such as participatory-based simulation modelling can be more valuable when it is effective in posing a wide range of 'what if' questions asked by farmers, as well as providing good insights and answering farmers' climate risk management concerns (Carberry et al., 2004; Whitbread et al., 2010). In this way it can help farmers to see in practice how a simulation and modelling approach is helpful in guiding their decision making in the context of the long-term characteristics of climate variability (Dimes et al., 2003; Cooper et al., 2008). In the study, farmers were only involved in the participatory diagnosis stage that allowed better insights into their decision making and the challenge of managing climate variability and risk, as well as where the opportunities for improvement may lie that enable them to better respond to this environmental stressor. In the study, a simulation and modelling approach was employed without engaging farmers in the process of exploring the various management scenarios for identifying the potential management options for future recommendations. Participatory-based simulation modelling, however, has been rarely acknowledged for solving actual agricultural problems and affecting farmer decision-making (Carberry et al., 2004). The FARMSCAPE (Farmers', Advisors', Researchers' Monitoring, Simulation, Communication and Performance Evaluation) approach can be taken as a typical example of an interface that takes a systems approach one step further by coupling simulation of relevant farming events and actions into the context of farmers' learning and solving problems that lead to on-ground changes in management practices (Carberry et al., 2002). Moreover, it aroused interest amongst smallholder farmer groups as they gained confidence in the plausibility of simulation results and potential usefulness of the models (Hochman et al., 2017a and b), which can potentially lead farmers to engage in discussions about how the model can be used to answer a range of "what-if" questions and subsequent exploration of management opportunities (Dimes et al., 2003; Cooper et al., 2008). This method, in which participatory action-research is combined with a soft systems approach (Checkland, 1981), was adopted by engaging farmers as the key decision makers in their management situation while using hard systems tools such as complex dynamic-based crop models for simulation analysis of diverse management options at the local field level for assisting farmers to make informed cropping decisions in the face of variable and uncertain climate (Carberry et al., 2002; McCown et al., 2009). Its success seems to be related to the fact that farmers and their extension advisors have played key roles through their direct participation in the design and implementation of the approach, including adjustments to the crop model based on farmers' recommendations and demands depending on each farmer's particular situation. As such, these results were achieved following a lengthy investment in research and development (Le Gal et al., 2011).

Smallholder farming systems are complex as they commonly have several components (e.g., crop and livestock production and capital and labor investments) which are tightly interlinked towards achieving a multitude of goals (e.g., food self-sufficiency, income generation and risk management). In a complicated and dynamic smallholder farming systems in SSA where a number of alternative crop and livestock enterprises are the key components of the system, household farms face multiple trade-offs between objectives when deciding on the allocation of their limited resource to competing production activities (Tittonellet al., 2007a; Rodriguez et al., 2011). Therefore, it is insufficient to focus on one crop, as changes in the productivity of individual crops might not reflect the fact that farmers effectively manage their limited resources to satisfy a number of objectives at the whole-farm level (Power et al., 2011). For analysing interventions on the performance of a system at the crop or the field or the whole-farm level, it is important considering several indicators relevant to the system properties under study. However, one of the limitations of the study was that the various management scenarios were not evaluated using multiple criteria such as economic benefit and water and nutrient productivity as well as sustainability of the farming system that provide situation specific trade-offs information between competing objectives, such as enhancing profit, food security, livelihoods; rather than simply increasing crop yields (Tittonell et al., 2007a). In the context of diverse and complex bio-physical and socio-economic system, integrative assessment of the farming systems, in which farmers are engaged in participatory discussions about the long-term simulation scenarios, can guide farmers' decision on how to better target practices, and allocate household investments to maximise benefits while minimising trade-offs (e.g., risk) (Van Wijk et al., 2009; Dimes et al., 2015). In other words, 'multiple options' rather than a 'single best-bet solution' approach to technology identification and development is a feasible approach that can potentially help to better target technological recommendations and system changes that are suited to specific level of resource endowment, risk preference and livelihood strategy of local farmers (Giller et al., 2011a and b). To achieve this, integration of socio-economic and bio-physical approaches can provide an opportunity to quantify the impacts of investments on alternative technological interventions in terms of levels of food security, risk, household profits, and environmental outputs (Rodriguez and Sadras, 2011; Kalaugher et al., 2013). To fully exploit the linkages between components of the system at a farm scale, it is essential, however, that crop simulation models are configured for generating information that can help farmers envisage what they can achieve from what has been simulated. This will allow farmers to explore the impact of alternative allocation of limited production resources on their farms based on their multiple objectives across a number of alternative farm enterprises at the whole farm level, which can vary depending on farmers' capacity, capability and preferences (Power et al., 2011; Rodriguez et al., 2014).

In recent years, a better understanding of farmer differences has gained widened awareness in developing possible opportunities according to farmers' situations who are varying in their cropping decisions to manage and allocate limited resources to satisfy multiple objectives across a number of alternative enterprises (Rodriguez and Sadras, 2011). Assessment of the feasibility of proposed management alternatives for smallholder farmers require having a clear understanding of, and insight into, the management aspects of the household in relation to the bio-physical aspects of the production system (Thornton and Herrero, 2001). Therefore, adoption of technologies and practices do not only depend on their technical relevance in improving yields, rather on several decisive factors that can be grouped into broad categories such as technology-specific (e.g., soil type and management regime), household-specific (e.g., farmer perceptions, resource endowment, and household size) and bio-physical-specific in a given policy framework and institutional context, particularly the farmer's market access and farmer's market participation (Rodriguez and Sadras, 2011). Therefore, it appears critical to model several type of household typologies and their collective interactions with markets using advanced integrative analysis tools in combination with in-depth household survey information (Valbuena et al., 2010; An, 2012). Therefore, model integration into local research and extension platforms in Ethiopia needs to be part of a wider intervention that considers the whole farm scale.

For developing locally relevant and effective interventions according to the needs of smallholder farmers, promotion of innovation system where researchers, extension advisors and farmers can create good partnerships and strong synergy between them to develop and adapt technologies has been definitely required for enabling these key actors to work closely and achieve great success in agricultural RD&E endeavours (Twomlow et al., 2010; Thierfelder and Wall, 2011). In particular, the fragmented organisation of agricultural production renders it difficult for researchers to interact with a large range of farmers, especially when they are not institutionally organised. Therefore, designing and implementing specific mechanisms such as communication platforms between researchers, farmers and advisors may be useful to identify common problems and to discuss the value of alternative solutions (Hocdé et al., 2009). Integration of multidisciplinary teams in trans-disciplinary research approaches, as well as participatory approaches, are therefore required to allow for sustainable intensification of agricultural production (Meinke et al., 2009: Rodriguez and Sadras, 2011; van Ginkel et al., 2013; Giller et al., 2015). A proactive approach that combines promising technological, institutional and policy solutions to manage the risks within vulnerable communities needs to be implemented by institutions operating from a community to national level. This type of approach is considered to be the way forward for managing climate variability effectively (Shiferaw et al., 2014). In general, emphasis should be given to the need for substantial investments in institutional structure, agricultural RD&E, access to finance, and ways to better manage and reduce risks in both agro-technical as well as socio-economic terms if smallholder farmers in Ethiopia are to adopt technology that can close the huge yield gaps (World Bank, 2008, Keating et al., 2010). As a result, future food security and the livelihoods of the farming community can be enhanced in risk-prone and semi-arid regions of Ethiopia.

Reference

Abate T, Shiferaw B, Menkir A, Wegary D, KebedeY, Tesfaye K, et al. 2015. Factors that transformed maize productivity in Ethiopia. Food Security, 7(5): 965-981.

Abebe G. 2005. Participatory selection of drought tolerant maize varieties using mother and baby methodology: A case study in the semi-arid zones of the Central Rift Valley of Ethiopia. African Crop Science Conference Proceedings, 7: 1479-1485.

Abegaz A, van Keulen H. 2009. Modelling soil nutrient dynamics under alternative farm management practices in the Northern Highlands of Ethiopia. Soil & Tillage Research, 103: 203-215.

Adam M, Ewert F, Leffelaar PA, Corbeels M, Van Keulen H, Wery J. 2010. CROSPAL 0software that uses agronomic expert knowledge to assist modules selection for crop growth simulation. Environmental Modelling & Software, 25: 946-955.

Adam M, Van Bussel LGJ, Leffelaar PA, Van Keulen H, Ewert F. 2011. Effects of modelling detail on simulated potential crop yields under a wide range of climatic conditions. Ecological Modelling, 222: 131-143.

Adenew B. 2004. The food security role of agriculture in Ethiopia. Journal of Agricultural and Development Economics, 1: 138-153.

Adimassu Z, Kessler A, Hengsdijk H. 2012. Exploring determinants of farmers' investments in land management in the Central Rift Valley of Ethiopia. Applied Geography, 35: 191-198.

Adimassu Z, Kessler A, Yirga C, Stroosnijder L. 2013. Farmers’ perceptions of land degradation and their investments in land management: a case study in the Central Rift Valley of Ethiopia. Environmental Management, 51: 989-998.

Admassu H, Mahoo H, Rwehumbiza F, Tumbo S, Mogaka H. 2014. Enhancing response farming for strategic and tactical management of risks of seasonal rainfall variability. African Crop Science Journal, 22: 941-950**.**

Ahmed MM, Rohrbach DD, Gono LT, Mazhangara EP, Mugwira L, Masendeke DD, Alibaba S. 1997. Soil fertility management in communal areas of Zimbabwe: current practices, constraints and opportunities for change. Southern and Eastern Africa Region Working Paper No. 6. ICRISAT, Bulawayo, Zimbabwe.

Ahuja LR, Hanson JD, Shaffer MJ, Liwang Ma. (eds.). 2000. Root Zone Water Quality Model: Modeling Management Effects on Water Quality and Crop Production. Water Resources Publications, Highlands Ranch Co.

Akponikpè PI, Gérard B, Michels K, Bielders C. 2010. Use of the APSIM model in long term simulation to support decision making regarding nitrogen management for pearl millet in the Sahel. European Journal of Agronomy, 32: 144-154.

Akram-Lodhi AH, Kay C. 2010. Surveying the agrarian question (part 1): unearthing foundations, exploring diversity. The Journal of Peasant Studies, 37: 177-202.

An L. 2012. Modeling human decisions in coupled human and natural systems: review of agent-based models. Ecological Modelling, 229: 25-36.

Anandajayasekeram PR, Puskur, Workneh S, Hoekstra D. 2008. Concepts and practices in agricultural extension in developing countries: A source book. IFPRI (International Food Policy Research Institute), Washington, DC, USA, and ILRI (International Livestock Research Institute), Nairobi, Kenya.

Anderson JR. 1974. Risk efficiency in the interpretation of agriculture production research. Review of Marketing and Agricultural Economics, 42: 131-184

Anderson JR, Dillon, JL, Hardaker, JB. 1977. Agricultural Decision Analysis, Iowa State University Press, Ames.

Anderson WK, Heinrich A, Abbotts R. 1996. Long-season wheats extend sowing opportunities in the central wheat belt of Western Australia. Australian Journal of Experimental Agriculture, 36: 203-208.

Andrade FH, Echarte L, Rizzalli R, Della Maggiora A, Casanovas M. 2002. Kernel number prediction in maize under nitrogen or water stress. Crop Science, 42: 1173-1179.

Araya A, Hoogenboom G, Luedeling E, Kiros MH, Isaya KL, Martorano G. 2015. Assessment of maize growth and yield using crop models under present and future climate in south western Ethiopia. Agricultural and Forest Meteorology, 214-215: 252-265.

Araya A, Stroosnijder L. 2011. Assessing drought risk and irrigation need in northern Ethiopia. Agricultural and Forest Meteorology, 151: 425-436.

Archontoulis SV, Miguez FE, Moore KJ. 2014. Evaluating APSIM Maize, Soil Water, Soil Nitrogen, Manure, and Soil Temperature Modules in the Midwestern United States. Agronomy Journal, 106: 1025-1040.

Asseng S, Ewert F, Rosenzweig C, Jones J, Hatfield J, Ruane A, Boote K, Thorburn P, Rötter R, Cammarano D. 2013. Uncertainty in simulating wheat yields under climate change. Nature Climate Change, 3: 827-832.

Ati OF, Stigter CJ, Olandipo EO. 2002. Comparison of methods to determine the onset of the growing season in northern Nigeria. International Journal of Climate, 22: 731-742.

Aumann CA. 2007. A methodology for developing simulation models of complex systems. Ecological Modelling, 202(3): 385-396.

Ayenew T. 2007. Water management problems in the Ethiopian Rift: challenges for development. Journal of African Earth Sciences, 48: 222-236.

Bacic ILZ, Bregt AK, Rossiter DG. 2006. A participatory approach for integrating risk assessment into rural decision-making: a case study in Santa Catarina, Brazil. Agricultural Systems, 87: 229-244.

Badu-Apraku B, Oyekunle M, Menkir A, Obeng-Antwi K, Yallou CG, Usman IS, Alidu H. 2013. Comparative performance of early-maturing maize cultivars developed in three areas under drought stress and well-watered environments in West Africa. Crop Science, 53: 1298-1311.

Bänziger M. 2000. Breeding for drought and nitrogen stress tolerance in maize: from theory to practice. Mexico, D.F. CIMMYT.

Barnabás B, Jäger K., Fehér A. 2008. The effect of drought and heat stress on reproductive processes in cereals. Plant Cell Environ, 31: 11-38.

Barrett JR, Nearing MA. 1998. Humanization of decision support using information from simulations. In: Peart RM, Curry RB. (eds.). Agricultural systems modeling and simulation, Marcel Dekker, New York, pp. 1-18.

Barron J, Rockström J, Gichuki F, Hatibu N. 2003. Dry spell analysis and maize yields for two semi-arid locations in East Africa. Agricultural and forest meteorology, 117: 23-37.

Bationo A, Kihara J, Adesina A. 2012. Beyond bio-physical recommendations: towards a new paradigm. In: Kihara J. et al. (eds.). Improving Soil Fertility Recommendations in Africa using the Decision Support System for Agrotechnology Transfer (DSSAT). Springer, Dordrecht, The Netherlands, pp. 169-184.

Bawden RJ, Ison RL, Macadam RD, Packham RG, Valentine I. 1985. A research paradigm for systems agriculture. In: Remenyi JV. (ed.). Farming Systems Research: Australian Expertise for Third World Agriculture, ACIAR, Canberra, pp. 31-42.

BeckerM, George T. 1995. Nitrogen fixation response of stem- and root-nodulating Sesbania species to flooding and mineral nitrogen. Plant and Soil, 175: 189-196.

Beebe J. 1995. Basic concepts and techniques of rapid appraisal. Human organization, 54: 42-51.

Beiragi MA, Khorasani SK, Shojaei SH, Dadresan M, Mostafavi K, Golbashy M. 2011. A study on effects of planting dates on growth and yield of 18 corn hybrids (*Zea mays* L.). American Journal of Experimental Agriculture, 1: 110-120.

Bellon MR. 2001. Participatory Research Methods for Technology Evaluation: A Manual for Scientists Working with Farmers. Mexico, DF, CIMMYT.

Bennie ATP, Hensley M. 2001. Maximizing precipitation utilization in dryland agriculture in South Africa–a review. Journal of Hydrology, 241: 124-139.

Benson T. 1999. An Investigation of the Data Available in Malawi for Conducting Crop Model Simulations. Risk management for maize farmers in drought-prone areas of Southern

Africa. In: Proceedings of a Workshop, Kadoma Ranch (Zimbabwe), 1-3 Oct 1997, Zimbabwe, CIMMYT.

Bentley JW. 1994. Facts, fantasies, and failures of farmer participatory research. Agriculture and human values, 11: 140-150.

Berzsenyi Z, Lap DQ. 2001. Effect of sowing time and N fertilisation on the yield and yield stability of maize (*Zea mays* L.) hybrids between 1991–2000. Acta Agronomica Hungarica, 50: 309-331.

Biazin B, Sterk G, Temesgen M, Abdulkedir A, Stroosnijder L. 2012. Rainwater harvesting and management in rainfed agricultural systems in sub-Saharan Africa —A review. Physics and Chemistry of the Earth, 47-48: 139-151.

Biazin B, Stroosnijder L. 2012. To tie or not to tie ridges for water conservation in Rift Valley drylands of Ethiopia. Soil & Tillage Research, 124: 83-94.

Biazin B, Stroosnijder L, Temesgen M, Abdulkadir A, Sterk G. 2011. The effect of long-term Maresha ploughing on soil physical properties in the central Rift Valley of Ethiopia. Soil & Tillage Research, 111: 115-122.

Biggs SD. 1988. Resource poor farmer participation in research: a synthesis of experiences from nine national agricultural research systems. OFCOR Comparative Study Paper No. 3. ISNAR, The Hague.

Birhane G, Wortmann C, Mamo M, Gebrekidan H, Belay A. 2006. Micro-basin tillage for grain sorghum production in semiarid areas of Northern Ethiopia. Agronomy Journal, 98: 124-128.

Bogale G, Wegary D, Tilahun, L, Gebre D. 2011. Maize improvement for low-moisture stress areas of Ethiopia: In: Worku M, Twumasi-Afriyie S, Wolde L, Tadesse B, Demisie G, Bogale G, Wegary D, Prasanna BM. (eds.). Proceedings of the Third National Maize Workshop of Ethiopia, "Meeting the Challenges of Global Climate Change and Food Security through Innovative Maize Research", 18-20 April, 2011. Addis Ababa, Ethiopia. EIAR, CIMMYT, pp. 35-42.

Bontkes TES, Singh U, Chude VO. 2001. Problems and opportunities in adopting system tools for decision-making related to soil fertility improvement in Africa. Paper presented at the INMR symposium, CIAT, Cali, Columbia.

Bontkes TES, Wopereis MCS. (eds.). 2003. Decision support tools for smallholder agriculture in Sub-Saharan Africa: a practical guide. IFDC-CTA publication, Muscle Soals.

Boomsma CR, Vyn TJ. 2008. Maize drought tolerance: Potential improvements through arbuscular mycorrhizal symbiosis? Field Crops Research, 108: 14-31.

Boote KJ, Jones JW, Pickering NB. 1996. Potential uses and limitations of crop models. Agronomy Journal, 88: 704-716.

Boote KJ, Jones JW, White JW, Asseng S, Lizaso JI. 2013. Putting mechanisms into crop production models. Plant, Cell & Environment, 36: 1658-1672.

Boote KJ, Porter C, Jones JW, Thorburn PJ, Kersebaum KC, Hoogenboom G, White JW, Hatfield JL. 2015. Sentinel site data for crop model improvement, definition and characterization, improving modeling tools to assess climate change effects on crop response. American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America, Madison, WI.

Bortiri E, Hake S. 2007. Flowering and determinacy in maize. Journal of Experimental Botany, 58: 909-916.

Bot AJ, Nachtergaele F, Young A. 2000. Land resource potential and constraints at regional and country levels. World Soil Resources Reports. Rome, FAO, pp. 17-24.

Bouma J, Jones JW. 2001. An international collaborative network for agricultural systems applications (ICASA). Agricultural Systems, 70(2): 355-368.

Branney P, Malla Y, Neupane H. 2000. Learning by doing: participatory research with forest user groups in Nepal. Forestry, Forest Users and Research: New ways of Learning. ETFRN, Wageningen, The Netherlands, pp. 97-108.

Brossier J, Hubert H. 2000. Integration of bio-technical, economic and social sciences. Proceedings of the2nd European IFSA Symposium, pp. 41-65.www.ifsa—europe.org.

Bruce WB, Edmeades GO, Barker TC. 2002. Molecular and physiological approaches to maize improvement for drought tolerance. Journal of Experimental Botany, 53: 13-25.

Cacho OJ, Bywater AC, Dillon JL. 1999. Assessment of production risk in grazing models. Agricultural Systems, 60: 87-98.

Çakir R. 2004. Effect of water stress at different development stages on vegetative and reproductive growth of corn. Field Crops Research, 89: 1-16.

Campos H, Cooper M, Habben JE, Edmeades GO, Schussler JR. 2004. Improving drought tolerance in maize: a view from industry. Field Crops Research, 90: 19-34.

Carberry PS. 2001. Can science rigour and industry relevance both be achievable in participatory action research? Agricultural Science, 14: 25-31

Carberry P, Abrecht D. 1991. Tailoring crop models to the semi-arid tropics. In: Muchow RC, Bellamy JA. (eds.). Climatic risk in crop production: Models and management in the semi-arid tropics and sub-tropics. CAB International, Wallingford, pp. 157-182.

Carberry P, Gladwin C, Twomlow S. 2004. Linking simulation modelling to participatory research in smallholder farming systems. ACIAR, pp. 32-46.

Carberry PS, Hochman Z, Hunt JR, Dalgliesh NP, McCown RL, Whish JPM, Robertson MJ, Foale MA, Poulton PL, Rees Hv. 2009. Re-inventing model-based decision support with

Australian dryland farmers. 3. Relevance of APSIM to commercial crops. Crop and Pasture Science, 60: 1044-1056.

Carberry PS, Hochman Z, McCown RL, Dalgliesh NP, Foale MA, Poulton PL, Hargreaves JNG, Hargreaves DMG, Cawthray S, Hillcoat N, Robertson MJ. 2002. The FARMSCAPE approach to decision support: farmers', advisers', researchers' monitoring, simulation, communication and performance evaluation. Agricultural Systems, 74: 141-177.

Carberry PS, Liang W, Twomlow S, Holzworth DP, Dimes JP, McClelland T, Huth NI, Chen F, Hochman Z, Keating BA. 2013. Scope for improved eco-efficiency varies among diverse cropping systems. Proceedings of the National Academy of Sciences 110, 21: 8381-8386.

Castelan-Ortega OA, Fawcett RH, Arriaga-Jordan C, Herrero M. 2003. A decision support system for smallholder campesino maize-cattle production systems of the Toluca Valley in Central Mexico. Part I: Integrating biological and socio-economic models into a holistic system. Agricultural Systems, 75: 1-21.

Castella JC, Trung TN, Boissau S. 2005. Participatory simulation of land-use changes in the northern mountains of Vietnam: the combined use of an agent-based model, a role-playing game, and a geographic information system. Ecology and Society, 10(1): 27. http://www.ecologyandsociety.org/vol10/iss1/art27/

Castellazzi MS, Wood GA, Burgess PJ, Morris J, Conrad KF, Perry JN. 2008. A systematic representation of crop rotations. Agricultural Systems, 97: 26-33.

Challinor AJ, Ewert F, Arnold S, Simelton E, Fraser E. 2009. Crops and climate change: progress, trends, and challenges in simulating impacts and informing adaptation. Journal of Experimental Botany, 60: 2775-2789.

Chambers R. 1989. Reversals, Institutions and Change. In: Chambers R, Parcey A, Thrupp LA. (eds.). Farmer-First: Farmer Innovation and Agricultural Research, Intermediate Technology Publications, London, pp. 185-191.

Chambers R. 1994. Paradigm shifts and the practice of participatory research and development. Working Paper No. 2. Institute of Development Studies, Sussex, UK.

Chapman SC, Cooper M, Hammer GL. 2002. Using crop simulation to generate genotype by environment interaction effects for sorghum in water-limited environments. Australian Journal of Agricultural Research, 53: 379-389.

Chapman SC, Cooper M, Podlich D, Hammer GL. 2003. Evaluating plant breeding strategies by simulating gene action and dryland environment effects. Agronomy Journal, 95: 99-113.

Checkland PB. 1981. Systems thinking, systems practice. John Wiley and Sons, London.

Checkland PB, Scholes P. 1990. Soft system methodology in action. Wiley, Chichester.

Chenu K, Chapman SC, Tardieu F, McLean G, Welcker C, Hammer GL. 2009. Simulating the yield impacts of organ-level quantitative trait loci associated with drought response in maize: A gene-to-phenotype" modeling approach. Genetics, 183: 1507-1523.

Chenu K, Cooper M, Hammer GL, Mathews KL, Dreccer MF, Chapman SC. 2011. Environment characterization as an aid to wheat improvement: interpreting genotype-environment interactions by modelling water-deficit patterns in North-Eastern Australia. Journal of Experimental Botany, 62: 1743-1755.

Chivenge P, Vanlauwe B, Six J. 2011. Does the combined application of organic and mineral nutrient sources influence maize productivity? A meta-analysis. Plant and Soil, 342: 1-30.

Coe R, Stern RD. 2011. Assessing and addressing climate-induced risk in sub-Saharan rainfed agriculture: Lessons learned. Experimental Agriculture, 47: 395-410.

Colin JP, Crawford EW. 2000. Economic perspectives in agricultural systems analysis. Review of agricultural economics, 22: 192-216.

Collinson MP. 2000. Introduction. In: Collinson MP. (ed.). A History of Farming Systems Research. FAO, Rome and CABI Publishing, Wallingford, pp. 1-4.

Conway D. 2000. Some aspects of climate variability in the North East Ethiopian Highlands-Wollo and Tigray. SINET-Ethiopian Journal of Science, 23: 139-161.

Conway D, Schipper ELF. 2011. Adaptation to climate change in Africa: Challenges and opportunities identified from Ethiopia. Global Environmental Change, 21: 227-237.

Cooper P, Coe R. 2011. Assessing and addressing climate-induced risk in Sub-Saharan rainfed agriculture. Experimental Agriculture, 47: 179-184.

Cooper P, Dimes J, Rao K, Shapiro B, Shiferaw B, Twomlow S. 2008. Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: an essential first step in adapting to future climate change? Agriculture, Ecosystems and Environment, 126: 24-35.

Cossani CM, Savin R, Slafer GA. 2010. Co-limitation of nitrogen and water on yield and resource-use efficiencies of wheat and barley. Crop and Pasture Science, 61: 844-851.

Craufurd PQ, Vadez V, Jagadish SK, Prasad PV, Zaman-Allah M. 2013. Crop science experiments designed to inform crop modeling. Agricultural and Forest Meteorology, 170: 8-18.

Croppenstedt A, Demeke M, Meschi MM. 2003. Technology adoption in the presence of constraints: the case of fertilizer demand in Ethiopia. Review of Development Economics, 7: 58-70.

Cross J. 2000. Risk management. In: Beer T (ed.). Risk Management and the Future, Australian Minerals and Energy Environment Foundation, Melbourne, Australia, pp. 1-12.

CSA (Central Statistical Agency of Ethiopia). 2010. Agricultural sample survey 2009/2010. Report on area and production of crops. CSA, Addis Ababa, Ethiopia.

CSA (Central Statistical Agency of Ethiopia). 2008. The 2007 population and housing census result report. CSA, Addis Ababa, Ethiopia.

Dalgliesh NP, Foale MA. 2005. Soil matters: Monitoring soil water and nutrients in dryland farming. Agric. Production Systems Res. Unit, Toowoomba, Australia.

Dardanelli JL, Bachmeier OA, Sereno R, Gil R. 1997. Rooting depth and soil water extraction patterns of different crops in a silty loam Haplustoll. Field Crops Research, 54: 29-38.

Darnhofer I, Bellon S, Dedieu B, Milestad R. 2010. Adaptiveness to enhance the sustainability of farming systems. A review. Agronomy for Sustainable Development, 30: 545-555.

Darnhofer I, Gibbon D. 2012. Farming Systems Research: An approach to inquiry. In: Darnhofer I, Gibbon D, Dedieu B. (eds.). Farming Systems Research into the 21st Century: The New Dynamic. Springer, Dordrecht, pp. 1-26.

David O, Markstrom SL, Rojas KW, Ahuja LR, Schneider IW. The Object Modeling System. In: Ahuja L, Ma L, Howell TA. (eds.). Agricultural System Models in Field Research and Technology Transfer, Lewis Publishers, Boca Raton, FL, USA, pp. 317-344.

Davidson AP. 1987. Does farming systems research have a future? Agricultural Administration and Extension, 24: 69-77.

Daynard T, Duncan WG. 1969. The black layer and grain maturity in corn. Crop Science, 9: 473-476.

Debelle T, Bogale T, Negassa W, Workayehu T, Liben M, Mesfin T, Mekonen B, Mazengia W. 2011. A review of fertilizer management research on maize in Ethiopia. In: Worku M, Twumasi-Afriyie S, Wolde L, Tadesse B, Demisie G, Bogale G, Wegary D, Prasanna BM. (eds.). Proceedings of the Third National Maize Workshop of Ethiopia, “Meeting the Challenges of Global Climate Change and Food Security through Innovative Maize Research”. 18-20 April, 2011. Addis Ababa, Ethiopia, EIAR and CIMMYT, pp. 46-55.

Delve RJ, Probert ME, Cobo J, Ricaurte J, Rivera M, Barrios E, Rao IM. 2009. Simulating phosphorus responses in annual crops using APSIM: model evaluation on contrasting soil types. Nutrient Cycling in Agroecosystems, 84: 293-306.

Demeke AB, Keil A, Zeller M. 2011. Using panel data to estimate the effect of rainfall shocks on smallholders’ food security and vulnerability in rural Ethiopia. Climate Change, 108: 185-206.

Dent J, Thornton P. 1988. The role of biological simulation models in farming systems research. Agricultural Administration and Extension, 29: 111-122.

de Rouw A. 2004. Improving yield and reducing risk in pearl millet farming in the African Sahel. Agricultural System, 81: 73-93.

Dessie G, Kleman J. 2007. Pattern and magnitude of deforestation in the south Central Rift Valley region of Ethiopia. Mount. Research & Development, 27: 162-168.

Devereux S. 2001. Livelihood insecurity and social protection: a re-emerging issue in rural development. Development policy review, 19: 507-519.

Devereux S. 2009. Why does famine persist in Africa? Food security, 1: 25-35.

de Wit CT. 1970. Dynamic concepts in biology. In: Setlik I. (ed.). Prediction and Measurement of Photosynthetic Activity. Proceedings of the IBP/PP Technical Meeting, Třebon, 14-21 September 1969. Pudoc, Wageningen, The Netherlands, pp. 17-23.

de Wit CT, Goudriaan J. 1978. Simulation of ecological processes. Simulation Monographs, Pudoc, Wageningen.

de Wit CT, Van Keulen H. 1987. Modelling production of field crops and its requirements. Geoderma, 40: 253-265.

Diga GM. 2005. Risk analysis for various sorghum planting windows under variable rainfall. Using seasonal climate outlook to advise on sorghum production in the Central Rift Valley of Ethiopia. Bloemfontein, South Africa, University of the Free State.

Dimes J. 2011. Formulating crop management options for Africa's drought-prone regions: taking account of rainfall risk using modeling. In: Bationo A, Waswa B, Okeyo JM, Maina F, Kihara JM. (eds.). Innovations as Key to the Green Revolution in Africa. Springer, The Netherlands, pp. 785-794.

Dimes J, Achien J, Mesfin T, Abeya T, Makoko B, Nhantumbo N, Rodriguez D. 2011. Evaluation of APSIM to simulate maize-bean cropping systems in eastern and southern Africa: an alternative approach. Australian Centre for International Agricultural Research, pp. 1-4.

Dimes J, Muza L, Malunga G, Snapp S. 2002. Trade-offs between investments in nitrogen and weeding: on-farm experimentation and simulation analysis in Malawi and Zimbabwe. Paper presented at the 7th Eastern and Southern Africa Regional Maize Conference and Symposium on Low-Nitrogen and Drought Tolerant Maize, February 11-15, 2002, Nairobi, Kenya, pp. 452-456.

Dimes J, Rodriguez D, Potgieter A. 2015. Raising productivity of maize-based cropping systems in eastern and southern Africa: Step-wise intensification options. In: Sadras VO, Calderni DF. (eds.). Crop Physiology: Applications for Genetic Improvement and Agronomy Vol. 2. Academic Press, pp. 93-110.

Dimes J, Twomlow S, Carberry P. 2003. Application of APSIM in smallholder farming systems in the semi-arid tropics. In: Struif Bontkes TE, Wopereis MCS. (eds.). Decision Support Tools for Smallholder Agriculture in Sub-Saharan Africa: A Practical Guide. Muscle Shoals, U.S.A., IFDC, and Wageningen, The Netherlands, CTA, pp. 85-99.

Dixit P, Cooper P, Dimes J, Rao K. 2011. Adding value to field-based agronomic research through climate risk assessment: A case study of maize production in Kitale, Kenya. Experimental Agriculture, 47: 317-338.

Dixon JA, Gibbon DP, Gulliver A. 2001. Farming systems and poverty: improving farmers' livelihoods in a changing world. Food & Agriculture Organization, Rome.

Donatelli M, Confalonieri R. 2011. Bio-physical models for cropping system simulation. Bio-Economic Models applied to Agricultural Systems. Springer, pp. 59-86.

Donatelli M, Russell G, Rizzoli AE, Acutis M, Adam M, Athanasiadis IN, Balderacchi M, Bechini L, Belhouchette H, Bellocchi G. 2010. A component-based framework for simulating agricultural production and externalities. Environmental and Agricultural Modelling. Springer, pp. 63-108.

Douthwaite B, Kuby T, van de Fliert E, Schulz S. 2003. Impact pathway evaluation: an approach for achieving and attributing impact in complex systems. Agricultural Systems, 78: 243-265.

Dregne HE, Peterson G, Unger P, Payne W. 2006. Historical perspectives. In: Peterson GA, Unger PW, Payne WA. (eds.). Dryland agriculture, Agronomy Monograph No. 23. American Society of Agronomy, Crop Science Society of America, Soil Science Society of America, Madison, Wisconsin, USA, pp 27-38.

Dreyer M, Renn O. 2011. Participatory Approaches to Modelling for Improved Learning and Decision-making in Natural Resource Governance: An Editorial. Environmental policy and governance, 21: 379-385.

Ebinger CJ, Yemane T, Woldegabriel G, Aronson, JL, Walter RC. 1993. Late Eocene–Recent volcanism and faulting in the southern main Ethiopian rift. Journal of the Geological Society, 150: 99-108.

Edmeades GO. 2008. Drought tolerance in maize: an emerging reality. In: James C. (ed.). Global Status of Commercialized Biotech/GM Crops. ISAAA Brief 39: ISAAA, pp. 197-217.

Edmeades GO, Baeziger M, Ribaut J. 2000. Maize improvement for drought-limited environments. In: Otegui ME, Slafer GA. (eds.). Physiological Basis for Maize Improvement. Food Products Press, New York, pp. 75-112.

Efeoğlu B, Ekmekci Y, Cicek N. 2009. Physiological responses of three maize cultivars to drought stress and recovery. South African Journal of Botany, 75: 34-42.

Engida M. 2000. A desertification convention based on moisture zones of Ethiopia. Ethiopian Journal of Natural Resources, 1: 1-9.

EPA (Environmental Protection Authority). 1998. Background Information on Drought and Desertification in Ethiopia. EPA, Addis Ababa, Ethiopia.

FAO. 2009. Global Agriculture Towards 2050. High Level Expert Forum. FAO, Rome.

FAO. 2008. The state of food insecurity in the world. High food prices and food security—threats and opportunities. Food and Agriculture Organization of the United Nations, Rome.

FAO. 2006. The state of food insecurity in the world 2006: eradicating world hunger—taking stock ten years after the World Food Summit. Food and Agriculture Organization of the United Nations, Rome.

FAO. 2000. Land resource potential and constraints at regional and country levels. World Soil Resources Rep. 90. FAO, Rome.

Fischer R, Byerlee D, Edmeades G. 2014. Crop yields and global food security: Will yield increases continue to feed the world? ACIAR Monograph 158. Canberra, ACT. Australian Centre for International Agricultural Research.

Flick U. 2002. Qualitative research: State of the art. Social science information, 41: 5-24.

Flora CB, Francis C, Collinson M. 2000. FSR in extension and policy formulation. A history of farming systems research. In: Collinson MP. (ed.). A History of Farming Systems Research. FAO, Rome and CABI Publishing, Wallingford, England, pp.139-168.

Folberth C, Gaiser T Abbaspour KC, Schulin R, Yang H. 2012. Regionalization of a largescale crop growth model for sub-Saharan Africa: Model setup, evaluation, and estimation of maize yields. Agriculture, Ecosystem and Environment, 151: 21-33.

Fosu-Mensah B, MacCarthy D, Vlek P, Safo E. 2012. Simulating impact of seasonal climatic variation on the response of maize (*Zea mays* L.) to inorganic fertilizer in sub-humid Ghana. Nutrient Cycling in Agroecosystems, 94: 255-271.

France J, Thornley JH. 1984. Mathematical models in agriculture. Butterworths and Co Ltd., UK.

Fujisaka S, Wortmann C, Admassu H. 1996a. Research: Help or Hindrance to Good Farmers in High Risk Systems? Agricultural Systems, 54: 137-152.

Fujisaka S, Wortman C, Admassu H. 1996b. Resource poor farmers with complex technical knowledge in high risk system in Ethiopia: Can research help? Journal of Farming Systems Research-Extension, 6: 1-14.

Gaddis E, Voinov A. 2008. Participatory modeling. Encyclopaedia of Ecology: 2651-2655.

Gadgil S, Rao PRS. 2000. Farming strategies for a variable climate–A challenge. Current science, 1203-1215.

Gadgil S, Rao PRS, Rao KN. 2002. Use of climate information for farm-level decision making: rainfed groundnut in southern India. Agricultural Systems, 74: 431-457.

Garedew E, Sandewall M, Söderberg U, Campbell BM. 2009. Land-use and land-cover dynamics in the Central Rift Valley of Ethiopia. Environmental Management, 44: 683-694.

Gaydon DS, Balwinder-Singh E, Poulton PL, Horan H, Akhter S, et al. 2017. Evaluation of the APSIM Model in Cropping Systems in Asia. Field Crops Research, 204: 52-75.

Getachew H, Tesfaye K. 2015. Analysis of risks in crop production due to climate change in the Central Rift Valley of Ethiopia. African Journal of Agricultural Research, 10: 1913-1922.

Getnet M, Hengsdijk H, Van Ittersum M. 2014. Disentangling the impacts of climate change, land use change and irrigation on the Central Rift Valley water system of Ethiopia. Agricultural Water Management, 137: 104-115.

Getnet M, Van Ittersum M, Hengsdijk H, Descheemaeker K. 2016. Yield gaps and resource use across farming zones in the Central Rift Valley of Ethiopia. Experimental Agriculture, 52(4): 493-517.

Gheysari M, Miriatifi SM, Bannayan M, Homaee M, Hoogenboom G. 2009. Interaction of water and nitrogen on maize grown for silage. Agricultural Water Management, 96: 809-821.

Gilbert E, Norman D, Winch F (eds.). 1980. Farming systems research: a critical appraisal. MSU Rural Development Paper- Department of Agricultural Economics, Michigan State University, USA.

Giller KE, Andersson JA, Corbeels M, Kirkegaard J, Mortensen D, Erenstein O, Vanlauwe B. 2015. Beyond conservation agriculture. Frontier in Plant Science, 6: 37-14.

Giller KE, Corbeels M, Nyamangara J, Triomphe B, Affholder F, Scopel E, et al. 2011a. A research agenda to explore the role of conservation agriculture in African smallholder farming systems. Field Crops Research, 124: 468-472.

Giller KE, Tittonell P, Rufino MC, et al. 2011b. Communicating complexity: Integrated assessment of trade-offs concerning soil fertility management within African farming systems to support innovation and development. Agricultural Systems, 104: 191-203.

Giller KE, Witter E, Corbeels M, Tittonell P. 2009. Conservation agriculture and smallholder farming in Africa: the heretics' view. Field Crops Research, 114: 23-34.

Gonzalez-Dugo V, Durand JL, Gastal F. 2010. Water deficit and nitrogen nutrition of crops. A review. Agronomy for Sustainable Development, 30: 529-544.

Goujard O, van den Berg M, Heffer P, Zingore S. 2011. Maize Intensification in Mozambique: Demonstrating to Farmers the Benefits of Better Land and Crop Management. International Fertilizer Correspondent International Potash Institute, Horgen, pp. 8-15.

Grassini P, van Bussel LG, Van Wart J, Wolf J, Claessens L, Yang H, Boogaard H, de Groot H, van Ittersum MK, Cassman KG. 2015. How good is good enough? Data requirements for reliable crop yield simulations and yield-gap analysis. Field Crops Research, 177: 49-63.

Grassini P, Yang H, Cassman KG. 2009. Limits to maize productivity in the western Corn Belt: a simulation analysis for fully irrigated and rainfed conditions. Agricultural and Forest Meteorology, 149: 1254-1265.

Grix J. 2010. The foundations of research. Palgrave Macmillan, London.

Gungula DT, Kling JG, Togun AO. 2003. CERES-maize predictions of maize phenology under nitrogen-stressed conditions in Nigeria. Agronomy Journal, 95: 892-899.

Haileslassie A, Priess J, Veldkamp E, Teketay D, Lesschend JP. 2005. Assessment of soil nutrient depletion and its spatial variability on smallholders’ mixed farming systems in Ethiopia using partial versus full nutrient balances. Agriculture, Ecosystems and Environment, 108: 1-16.

Hall B, Kidd J. 1978. Adult learning, a design for action: a comprehensive international survey. International Conference on Adult Education and Development, Dares Salaam, Sage Publications.

Hammer GL. 1998. Crop modelling: current status and opportunities to advance. Acta Horticulturae, 456: 27-36.

Hammer GL, Dong ZS, McLean G, Doherty A, Messina C, Schussler J, Zinselmeier C, Paszkiewicz S, Cooper M. 2009. Can changes in canopy and/or root system architecture explain historical maize yield trends in the U.S. Corn Belt? Crop Science, 49: 299-312.

Hammer GL, Jordan DR. 2007. An integrated systems approach to crop improvement. In: Spierts JHJ, Struik PC, van Laar HH. (eds.). Scale and Complexity in Plant Systems Research: Gene-Plant-Crop Relations. Springer, Dordrecht, The Netherlands, pp. 45-61.

Hammer GL, Kropff MJ, Sinclair TR, Porter JR. 2002. Future contributions of crop modelling—from heuristics and supporting decision making to understanding genetic regulation and aiding crop improvement. European Journal of Agronomy, 18: 15-31.

Hammer G., McLean G, Chapman SC, Zheng B, Doherty A, Harrison MT, van Oosterom E, Jordan D. 2014. Crop design for specific adaptation in variable dryland production environments. Crop Pasture Science. 65 (7): 614-626.

Hammer GL, Messina C, van Oosterom E, Chapman S, Singh V, Borrell A, Jordan D, Cooper M. 2016. Molecular Breeding for Complex Adaptive Traits: How Integrating Crop Ecophysiology and Modelling Can Enhance Efficiency. In Yin X, Struik PC. (eds.). Crop Systems Biology Narrowing the, Narrowing the Gaps between Crop Modelling and Genetics, Springer International Publishing, Switzerland, pp.147-162.

Hammer GL, Nicholls N, Mitchell C. 2000. Applications of seasonal climate forecasting in agricultural and natural ecosystems, Vol. 21, Springer Science & Business Media.

Hansen J. 2005. Integrating seasonal climate prediction and agricultural models for insights into agricultural practice. Philosophical Transactions of the Royal Society: Biological Sciences, 360: 2037-2047.

Hansen J, Jones J. 2000. Scaling-up crop models for climate variability applications. Agricultural Systems, 65: 43-72.

Hansen J, Marx S, Weber E. 2004. The role of climate perceptions, expectations, and forecasts in farmer decision making: The Argentine Pampas and South Florida. IRI Technical Report 04-01. International Research Institute for Climate Prediction, Palisades, New York.

Hansen S, Jensen H, Nielsen N, Svendsen H. 1991. Simulation of nitrogen dynamics and biomass production in winter wheat using the Danish simulation model DAISY. Fertilizer research, 27: 245-259.

Hardaker JB, Huirne RBM, Anderson JR, Lien G. 2004a. Coping with Risk in Agriculture 2nd edition, CABI Publishing, Oxford.

Hardaker JB, Lien G. 2010. Probabilities for decision analysis in agriculture and rural resource economics: the need for a paradigm change. Agricultural Systems, 103: 345-350.

Hardaker JB, Richardson JW, Lien G, Schumann KD. 2004b. Stochastic efficiency analysis with risk aversion bounds: a simplified approach. Australian Journal of Agricultural and Resource Economics, 48: 253-270.

Hassani H, Silva ES. 2015. A Kolmogorov-Smirnov based test for comparing the predictive accuracy of two sets of forecasts. Econometrics, 3: 590-609.

Hearn AB. 1994. OZCOT: A Simulation model for cotton crop management. Agricultural Systems, 44: 257-299.

Heinrich GM. 1993. Strengthening Farmer Participation through Farmer Groups: Experiences and Lessons from Botswana. OFCOR Discussion Paper No. 3, International Service for National Agricultural Research, The Hague, Netherlands.

Hengsdijk H, Jansen H. 2006. Agricultural development in the Central Ethiopian Rift valley: A desk-study on water-related issues and knowledge to support a policy dialogue. Plant Research International BV, Wageningen, pp. 1-25.

Hennink MM. 2007. International focus group research. Atlanta: Emory University.

Hochman ZH, Coutts JA, Carberry PS, McCown RL. 2000. The FARMSCAPE experience: Simulations aid participative learning in risky farming systems in Australia. In: Cerf M, Gibbons D, Hubert B, Ison R, Jiggins J, Paine MS, Roling N. (eds.). Cow up a Tree: Knowing and Learningfor Change in Agriculture: Case Studies from Industrialised Countries. INRA Editions, VersaillesCedex, France, pp. 175-188.

Hochman Z, Horan H, Reddy DR, Sreenivas G, Tallapragada C, Adusumilli R, Gaydon DS, Laing A, Kokic P, Singh KK, Roth CH. 2017a. Smallholder farmers managing climate risk in India: 2. Is it climate-smart? Agricultural Systems, 151: 61-72.

Hochman Z, Horan H, Reddy DR, Sreenivas G, Tallapragada C, Adusumilli R, Gaydon D, Singh KK, Roth CH. 2017b. Smallholder farmers managing climate risk in India: 1. Adapting to a variable climate. Agricultural Systems, 150: 54-66.

Hochman Z, van Rees H, Carberry PS, Hunt JR, McCown RL, Gartmann A, Holzworth D, van Rees S, Dalgliesh NP, Long W, Peake AS, Poulton PL, McClelland T. 2009. Re-inventing model-based decision support with Australian dryland farmers. 4. Yield Prophet® helps farmers monitor and manage crops in a variable climate. Crop Pasture Science, 60: 1057-1070.

Hoffmann V, Probst K, Christinck A. 2007. Farmers and researchers: How can collaborative advantages be created in participatory research and technology development? Agriculture and human values, 24(3): 355-368.

Hogarth RM. 2001. Educating intuition, University of Chicago Press, Chicago, IL, USA.

Holzworth DP, Huth NI, Zurcher EJ, Herrmann NI, McLean G, Chenu K, van Oosterom EJ, Snow V, Murphy C, Moore AD. 2014. APSIM–evolution towards a new generation of agricultural systems simulation. Environmental Modelling & Software, 62: 327-350.

Hoogenboom G, Jones J, Wilkens P, Batchelor W, Bowen W, Hunt L, Pickerong N, Singh U, Godwin D, Baer B. 1994. Crop model sp. 95-244. Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht, The Netherlands, pp. 9-39.

Hoogenboom G, Jones JW, Traore PCS, Boote KJ. 2012. Experiments and Data for Model Evaluation and Application In: Kihara J. et al. (eds.). Improving Soil Fertility Recommendations in Africa using the Decision Support System for Agrotechnology Transfer (DSSAT). Springer, Dordrecht, The Netherlands, pp. 9-18.

Hunt LA, Boote KJ. 1998. Data for model operation, calibration, and evaluation. In: Tsuji GY, Hoogenboom G, Thornton PK. (eds.). Understanding Options for Agricultural Production. Kluwer Academic Publishers, pp. 9-39.

IBM Corp. 2011. IBM SPSS Statistics for Windows, Version 20. International Business Machine Corp., Armonk, New York.

ICRA (International Center for Development Oriented Research in Agriculture). 1999. Livelihoods and drought coping strategies of households in Central Rift Valley of Ethiopia: Challenges for agricultural research. Working Document series no. 73. Wageningen, The Netherlands.

Ison RL. 2008. Systems thinking and practice for action research. In: Reason P, Bradbury H. (eds.). The Sage Handbook of Action Research Participative Inquiry and Practice, 2nd edition, Sage Publications, London, pp. 139-158.

Itanna F. 2005. Sulfur distribution in five Ethiopian Rift Valley soils under humid and semi-arid climate. Journal of Arid Environments, 62: 597-612.

Jagtap SS, Abamu FJ. 2003. Matching improved maize production technologies to the resource base of farmers in a moist savannah. Agricultural Systems, 76: 1067-1084

Jame Y, Cutforth H. 1996. Crop growth models for decision support systems. Canadian Journal of Plant Science, 76: 9-19.

Jamieson P, Porter J, Wilson D. 1991. A test of the computer simulation model ARCWHEAT1 on wheat crops grown in New Zealand. Field Crops Research, 27: 337-350.

Jansen H, Hengsdijk H, Legesse D, Ayenew T, Hellegers P, Spliethoff P. 2007. Land and water resource assessment in the Ethiopia central rift valley. Alterra-rapport 1587, Alterra, Wageningen.

Jiggins J. 1993. From technology transfer to resource management. In: Proceedings of the XVII International Grassland Congress, Palmerston North, New Zealand, pp. 615-622.

Jones CA, Kiniry JR. (eds.). 1986. CERES-Maize: A simulation model of maize growth and development. Texas AandM University Press, College Station, TX.

Jones J, Keating B, Porter C. 2001. Approaches to modular model development. Agricultural Systems, 70: 421-443.

Jones J, Luyten J. 1998. Simulation of biological processes. In: Peart RM, Curry RB. (eds.). Agricultural systems modeling and simulation, Marcel Dekker, New York, pp. 19-62.

Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt L, Wilkens PW, Singh U, Gijsman AJ, Ritchie JT. 2003. The DSSAT cropping system model. European Journal of Agronomy, 18: 235-265.

Just DR, Wolf S, Zilberman D. 2003. Principles of risk management service relations in agriculture. Agricultural Systems, 75: 199-213.

Kalaugher E, Bornman JF, Clark A, Beukes P. 2013. An integrated bio-physical and socio-economic framework for analysis of climate change adaptation strategies: The case of a New Zealand dairy farming system. Environmental Modelling and Software, 39: 176-187.

Kamanga B, Waddington S, Robertson M, Giller K. 2010. Risk analysis of maize-legume crop combinations with smallholder farmers varying in resource endowment in central Malawi. Experimental Agriculture, 46(1): 1-21.

Kamanga B, Waddington S, Whitbread A, Almekinders C, Giller K. 2014. Improving the efficiency of use of small amounts of nitrogen and phosphorus fertiliser on smallholder maize in central Malawi. Experimental Agriculture, 50: 229-249.

Kamara A, Ekeleme F, Chikoye D, Omoigui LO. 2009. Planting date and cultivar effects on grain yield in dryland corn production. Agronomy Journal, 101: 91-98.

Kamara A, Menkir A, Ajala S, Kureh I. 2005. Performance of diverse maize genotypes under nitrogen deficiency in the northern Guinea savanna of Nigeria. Experimental Agriculture, 41: 199-212.

Kanyama-Phiri G, Snapp S, Wellard K. 2000. Towards integrated soil fertility management in Malawi: Incorporating participatory approaches in agricultural research. Managing Africa's Soils No. 11, IIED, UK.

Kassie BT, Hengsdijk H, Rötter R, Kahiluoto H, Asseng S, Van Ittersum M. 2013a. Adapting to Climate Variability and Change: Experiences from Cereal-Based Farming in the Central Rift and Kobo Valleys, Ethiopia. Environmental management, 52: 1115-1131.

Kassie BT, Rötter R, Hengsdijk H, Asseng S, Van Ittersum M, Kahiluoto H, VanKeulen H. 2013b. Climate variability and change in the Central Rift Valley of Ethiopia: challenges for rainfed crop production. The Journal of Agricultural Science, 152(1): 58-74.

Kassie BT, Van Ittersum MK, Hengsdijk H, Asseng S, Wolf J, Rötter RP. 2014. Climate-induced yield variability and yield gaps of maize (*Zea mays* L.) in the Central Rift Valley of Ethiopia. Field Crops Research, 160: 41-53.

Kay R, Bawden R. 1996. Learning to be systemic: some reflections from a learning organization. Learning Organization, 3: 18-25.

Kandji ST, Verchot L, Mackensen J. 2006. Climate change and variability in the Sahel region: impacts and adaptation strategies in the agricultural sector. United Nations Environment Program (UNEP) and World Agroforestry Center (ICRAF), Nairobi.

Keshavarz M, Karami E. 2014. Farmers' decision-making process under drought. Journal of Arid Environments, 108: 43-56.

Keating BA, Carberry PS, Bindraban PS, Asseng S, Meinke H, Dixon J. 2010. Eco-efficient agriculture: concepts, challenges, and opportunities. Crop Science 50 (Suppl. 1), S-109.

Keating BA, Carberry PS, Hammer GL, Probert ME, Robertson MJ, Holzworth D, Huth NI, Hargreaves JNG, Meinke H, Hochman Z, Mclean G, Verburg K, Snow V, Dimes JP, Silburn, M, Wang E, Brown S, Bristow KL, Asseng S, Chapman S, McCown RL, Freebairn DM, Smith CJ. 2003. An overview of APSIM, a model designed for farming systems simulation. European Journal of Agronomy, 18: 267-288.

Keating BA, Godwin D, Watiki J. 1991. Optimising nitrogen inputs in response to climatic risk. In: Muchow RC, Bellamy JA. (eds.). Climatic Risk in Crop Production: Models and Management for the Semi-arid tropics and subtropics. CAB International, Wallingford, UK, pp. 329-358.

Keating BA, McCown RL. 2001. Advances in farming systems analysis and intervention. Agricultural Systems, 70: 555-579.

Keating BA, Waddington S, Shamudzarira Z, Grace P, Rohrbach D, Snapp S, Dimes J, Carberry PS, Robertson, MJ. 2000. Exploring farmer options for maize production strategies via scenario analyses using the APSIM model- an example of the approach (Risk Management Working Paper Series 00/02). CIMMYT, Mexico.

Keating BA, Wafula BM, Watiki JM. 1992. Exploring strategies for increased productivity– the case for maize in semi-arid Eastern Kenya. In: Probert ME. (ed.). A Search for Strategies for Sustainable Dryland Cropping in Semi-Arid Eastern Kenya. ACIAR Proceedings No. 41. Canberra, Australia, Australian Centre for International Agricultural Research, pp. 90-101.

Keating B, Wafula B, Watiki J, Karanja D. 1993. Dealing with climatic risk in agricultural research-a case study modelling maize in semi-arid Kenya: Australian Centre for International Agricultural Research, pp. 105-105.

Kihupi N, Kingamkono R, Dihenga H, Kingamkono M, Rwamugira W. 2003. Integrating indigenous knowledge and climate forecasts in Tanzania. In: Vogel C, O'Brien K. (eds.). Coping with climate variability: the use of seasonal climate forecasts in Southern Africa. Ashgate, Burlington, VT, pp. 155-169.

Kijne JW, Barker R, Molden DJ. 2003. Water Productivity in Agriculture: Limits and Opportunities for Improvement. IWMI and CABI Publisher, Wallingford (UK).

King C, Gunton J, Freebairn D, Coutts J, Webb I. 2000. The sustainability indicator industry: where to from here? A focus group study to explore the potential of farmer participation in the development of indicators. Australian Journal of Experimental Agriculture, 40(4): 631-642.

Kiniry JR. 1991. Maize phasic development. In: Hanks J, Ritchie JT. (eds.). Modeling Plant Soil systems. Agronomy Monograph no. 31, American Society of Agronomy, Crop Science Society of America, Soil Science Society of America, Madison, Wisconsin, USA, pp. 55-69.

Kisaka MO, Mucheru-Muna M, Ngetich FK, Mugwe JN, Mugendi DN, Mairura F, Muriuki J. 2015. Using APSIM-model as a decision-support-tool for long-term integrated-nitrogen-management and maize productivity under semi-arid conditions of Kenya. Experimental Agriculture, 1-21.

Klerkx L, van Mierlo B, Leeuwis C. 2012. Evolution of systems approaches to agricultural innovation: Concepts, analysis and interventions. In: Darnhofer I, Gibbon D, Dedieu B. (eds.). Farming Systems Research into the 21st century: The new dynamic. Dordrecht, Springer, pp. 457-483.

Knack S, Keefer K. 1997. Does social capital have an economic payoff? A cross-country investigation. The Quarterly Journal of Economics, 112: 1251-1288.

Korecha D. 2002. Climate Atlas of Ethiopia. Drought Monitoring Center. Nairobi, Kenya.

Korecha D. 1999. Seasonal rainfall prediction over Ethiopia. (June to September 1999). Report: Capacity Building Workshop for the Eastern Africa sub-region. Drought Monitoring Center, 2-22 May, 1999, Nairobi, Kenya.

Korecha D, Sorteberg A. 2013. Validation of operational seasonal rainfall forecast in Ethiopia. Water Resources Research, 49: 7681-7697.

Kropff MJ, Bouma J, Jones JW. 2001. Systems approaches for the design of sustainable agro-ecosystems. Agricultural Systems, 70: 369-393.

Kropff MJ, Spitters CJT. 1992. An eco-physiological model for interspecific competition, applied to the influence of Chenopodium album L. on sugar beet. I. Model description and parameterization. Weed Research, 32(6): 437-450.

Kropff MJ, Van Laar H, Matthews RB. 1994. ORYZA1: An ecophysiological model for irrigated rice production. SARP Research Proceedings. IRRI, Wageningen.

Krueger RA, Casey MA. 2002. Designing and conducting focus group interviews. Social analysis, selected tools and techniques, 4(23): 4-24.

Kucharik CJ. 2008. Contribution of planting date trends to increased maize yields in the central United States. Agronomy Journal, 100: 328-336.

Kumudini S, Andrade FH, Boote KJ, Brown GA, Dzotsi KA, Edmeades GO, Gocken T, Goodwin M, Halter AL, Hammer GL, et al. 2014. Predicting Maize Phenology: Intercomparison of Functions for Developmental Response to Temperature. Agronomy Journal, 106: 2087-2097.

Kumwenda JDT, Waddington SR, Snapp SS, Jones RB, Blackie MJ. 1997. Soil fertility management in Southern Africa. In: Byerlee D, Eicher CK. (eds.). Africa's Emerging Maize Revolution. Boulder, CO, USA: Lynne Rienner, pp. 157-172.

Le Gal PY, Dugué P, Faure G, Novak S. 2011. How does research address the design of innovative agricultural production systems at the farm level? A review. Agricultural Systems, 104: 714-728.

Le Gal PY, Merot A, Moulin CH, Navarrete M, Wery J. 2010. A modelling framework to support farmers in designing agricultural production systems. Environmental Modelling and Software, 25: 258-268.

Lemenih M, Itanna F. 2004. Soil carbon stocks and turnovers in various vegetation types and arable lands along an elevation gradient in southern Ethiopia. Geoderma, 123: 177-188.

Likert R. 1932. A technique for the measurement of attitudes. Archives of Psychology, 140: 5-53.

Lisson S, MacLeod N, McDonald C, Corfield J, Pengelly B, Wirajaswadi L, Rahman R, Bahar S, Padjung R, Razak N. 2010. A participatory, farming systems approach to improving Bali cattle production in the smallholder crop–livestock systems of Eastern Indonesia. Agricultural Systems, 103: 486-497.

Liu WZ, Zhang XC. 2007. Optimizing water and fertilizer input using an elasticity index: A case study with maize in the loess plateau of china. Field Crops Research, 100: 302-310.

Liu Y, Wang E, Yang X, Wang J. 2010. Contributions of climatic and crop varietal changes to crop production in the North China Plain, since 1980s. Global Change Biology, 16(8): 2287-2299.

Loewer O, Peart R, Bruce R. 1998. GRAZE: a beef-forage model of selective grazing. Agricultural systems modeling and simulation, pp. 301-417.

Long W, Cooper I. 2011. Farmer decision making in rainfed farming systems – The role of Consultants, Farming systems Groups and Decision Support Systems in Australia. In: Tow P, Cooper I, Partridge I, Birch C. (eds.). Rainfed Farming Systems. Springer, Dordrecht, The Netherlands, pp. 943-968.

Loomis RS, Rabbinge R, Ng E. 1979. Explanatory models in crop physiology. Annual Review of Plant Physiology, 30: 339-367.

Lopes M, Araus J, van Heerden PD, Foyer C. 2011. Enhancing drought tolerance in C4 crops. Journal of Experimental Botany, 62: 3135-3153.

López-Ridaura S, van Keulen H, Giller KE. 2006. Designing and evaluating alternatives for more sustainable natural resource management in less-favoured areas. In: Ruben R, Pender, J, Kuyvenhoven A. (eds.). Sustainable Poverty Reduction in Less-favoured Areas. CABI Publishing, Wallingford, UK.

Lynam T, de Jong W, Shell D, Kusumanto T, Evans K. 2007. A review of tools for incorporating community knowledge, preferences, and values into decision making in natural resources management. Ecology and Society 12(1):5. http://www.ecologyandsociety.org/vol12/iss1/art5/

MacCarthy DS, Akponikpe PBI, Narh S, Tegbe R. 2015. Modeling the effect of seasonal climate variability on the efficiency of mineral fertilization on maize in the coastal savannah of Ghana. Nutrient Cycling in Agroecosystems, 102: 45-64.

MacCarthy DS, Sommer R, Vlek PLG. 2009. Modeling the impacts of contrasting nutrient and residue management practices on grain yield of sorghum (*Sorghum bicolor* (L.) Moench) in a semi-arid region of Ghana using APSIM. Field Crops Research, 113: 105-115.

Mackenzie J, Tan PL, Hoverman S, Baldwin C. 2012. The value and limitations of Participatory Action Research methodology. Journal of Hydrology, 474: 11-21.

MacMillan T, Benton TG. 2014. Agriculture: Engage farmers in research. Nature, 509: 25-27.

Magombeyi MS, Taigbenu AE. 2008. Crop yield risk analysis and mitigation of smallholder farmers at quaternary catchment level: Case study of B72A in Olifants river basin, South Africa. Physics and Chemistry of the Earth, 33: 744-756.

Makin MJ, Kingham TJ, Waddams AE, Birchall CJ, Teffera T. 1975. Development prospects in the southern Rift Valley, Ethiopia. Land Resource Study, 21. LRD, Ministry of Overseas Development.

Marcelis L, Heuvelink E, Goudriaan J. 1998. Modelling biomass production and yield of horticultural crops: a review. Scientia Horticulturae, 74: 83-111.

Marenya PP, Barrett CB. 2009. Soil quality and fertilizer use rates among smallholder farmers in western Kenya. Agricultural Economics, 40: 561-572.
l
Marshall NA. 2010. Understanding social resilience to climate variability in primary enterprises and industries. Global Environmental Change, 20: 36-43.

Martin A, Sherington J. 1997. Participatory research methods–implementation, effectiveness and institutional context. Agricultural Systems, 55: 195-216.

Martin G, Theau JP, Therond O, Martin-Clouaire R, Duru M. 2011. Diagnosis and simulation: a suitable combination to support farming systems design. Crop and Pasture Science, 62: 328-336.

Matthews R, Stephens W, Hess T, Middleton T, Graves A. 2002. Applications of crop/soil simulation models in tropical agricultural systems. Advances in Agronomy, 76: 31-124.

Mavromatis T, Boote KJ, Jones JW, Irmak A, Shinde D, Hoogenboom G. 2001. Developing genetic coefficients for crop simulation models with data from crop performance trials. Crop Science, 41: 40-51.

McCown RL. 2012. A cognitive systems framework to inform delivery of analytic support for farmers' intuitive management under seasonal climatic variability. Agricultural Systems, 105: 7-20.

McCown RL. 2001. Learning to bridge the gap between science-based decision support and the practice of farming: Evolution in paradigms of model-based research and intervention from design to dialogue. Australian Journal of Agricultural Research, 52: 549-571.

McCown RL, Carberry PS, Dalgliesh NP, Foale MA, Hochman Z. 2012. Farmers use intuition to reinvent analytic decision support for managing seasonal climatic variability. Agricultural Systems, 106: 33-45.

McCown RL, Carberry PS, Hochman Z, Dalgliesh NP, Foale MA. 2009. Re-inventing model-based decision support with Australian dryland farmers. 1. Changing intervention concepts during 17 years of action research. Crop and Pasture Science, 60: 1017-1030.

McCown RL, Hammer GL, Hargreaves JNG, Holzworth DL, Freebairn DM. 1996. APSIM: A novel software system for model development, model testing, and simulation in agricultural systems research. Agricultural Systems, 50: 255-271.

McCown RL, Hochman Z, Carberry PS. 2002. Probing the enigma of the decision support system for farmers: learning from experience and from theory. Agricultural Systems, 74: 1-10.

McCown RL, Jones RK. 1992. Agriculture of semi-arid eastern Kenya: problems and possibilities. In: Probert M. (ed.). A search for a strategy for sustainable dryland cropping in semi-arid Eastern Kenya. Canberra, Australia: ACIAR, pp. 8-15.

McCown RL, Parton KA. 2006. Learning from the historical failure of farm management models to aid management practice. Part 2. Three systems approaches. Australian Journal of Agricultural Research, 57: 157-172.

Meinke H, Baethgen WE, Carberry PS, Donatelli M, Hammer GL, Selvaraju R, Stockle CO. 2001. Increasing profits and reducing risks in crop production using participatory systems simulation approaches. Agricultural Systems, 70: 493-513.

Meinke H, Howden SM, Struik PC, Nelson R, Rodriguez D, Chapman SC. 2009. Adaptation science for agricultural and natural resource management – Urgency and theoretical basis. Current Opinion in Environmental Sustainability, 1: 69-76.

Melkassa Research Centre. 2009. Annual Research Progress Report 2006-2008. Melkassa Research Centre, Melkassa, Ethiopia.

Meng Q, Hou P, Wu L, Chen X, Cui Z, Zhang F. 2013. Understanding production potentials and yield gaps in intensive maize production in China. Field Crops Research, 143: 91-97.

Merga F, Kim HK. 2014. Potential of conservation agriculture based maize-common bean system for increasing yield, soil moisture, and rainfall-use efficiency in Ethiopia. In: Verhulst N, Mulvaney M, Cox R, Van Loon J, Nichols V. (eds.). Compendium of Deliverables of the Conservation Agriculture Course. Mexico, CIMMYT, pp. 1-9.

Mertz O, Mbow C, Reenberg A, Diouf A. 2009. Farmers' perceptions of climate change and agricultural adaptation strategies in rural Sahel. Environmental Management, 43: 804-816.

Mesfin T, Tesfahunegn GB, Wortmann CS, Mamo M, Nikus O. 2010. Skip-row planting and tie-ridging for sorghum production in semiarid areas of Ethiopia. Agronomy Journal, 102: 745-750.

Mesfin T, Tesfahunegn GB, Wortmann CS, Nikus O, Mamo M. 2009. Tied-ridging and fertilizer use for sorghum production in semi-arid Ethiopia. Nutrient Cycling in Agroecosystems, 85: 87-94.

Meshesha DT, Tsunekawa A, Tsubo M. 2012. Continuing land degradation: Cause–effect in Ethiopia's Central Rift Valley. Land Degradation and Development, 23: 130-143.

Messina C, Hammer G, Dong Z, Podlich D, Cooper M. 2009. Modelling crop improvement in a GxExM framework via gene-trait-phenotype relationships. In: Sadras V, Calderini D. (eds.). Crop physiology: applications for genetic improvement and agronomy. Elsevier, The Netherlands, pp. 235-265.

Meza FJ, Silva D. 2009. Dynamic adaptation of maize and wheat production to climate change. Climatic change, 94: 143-156.

Meze-Hausken E. 2004. Contrasting climate variability and meteorological drought with perceived drought and climate change in northern Ethiopia. Climate Research, 27: 19-31.

Milestad R, Dedieu B, Darnhofer I, Bellon S. 2012. Farms and farmers facing change: The adaptive approach. Farming Systems Research into the 21st century: The new dynamic: Springer, pp. 365-385.

Mitchell PL. 1997. Misuse of regression for empirical validation of models. Agricultural Systems, 54: 313-326.

Moeller C, Asseng S, Berger J, Milroy SP. 2009. Plant available soil water at sowing in Mediterranean Environments-Is it a useful criterion to aid nitrogen fertiliser and sowing decisions? Field Crops Research, 114: 127-136.

Moeller C, Sauerborn J, de Voil P, Manschadi AM, Pala M, Meinke H. 2014. Assessing the sustainability of wheat-based cropping systems using simulation modelling: sustainability=42? Sustainability Science, 9: 1-16.

Moeller C, Smith I, Asseng S, Ludwig F, Telcik N. 2008. The potential value of seasonal forecasts of rainfall categories – Case studies from the wheatbelt in Western Australia's Mediterranean region. Agricultural and Forest Meteorology, 148: 606-618.

MoFED (Ministry of Finance and Economic Development). 2007. Ethiopia: Building on Progress: A Plan for Accelerated and Sustained Development to End Poverty (PASDEP). Annual Progress Report 2006/07, Addis Ababa.

Mohammed H, Mulatu K. 1993. Maize germplasm improvement for moisture stress areas. In: Tolessa B, Ransom JK. (eds.). Proceedings of the First National Maize Workshop of Ethiopia. Addis Ababa: IAR/CIMMYT, pp. 25-29.

Monteith JL. 1996. The quest for balance in crop modelling. Agronomy Journal, 88: 695-697.

Monteith JL. 1986. How do crops manipulate water supply and demand? Philosophical Transactions of the Royal Society, London A 316, 245/259.

Morgan, D. L. 1997. Focus groups as qualitative research, Sage.

Morris M, Kelly VA, Kopicki RJ, Byerlee D. 2007. Fertilizer use in African agriculture. Lessons learned and good practice guidelines. Directions in Development – Agriculture and Rural Development 39037. The World Bank, Washington DC. http://documents.worldbank.org/curated/en/2007/01/7462470/fertilizer-use-africanagriculture-lessons-learned-good-practice-guidelines

Moyo M, Mvumi B, Kunzekweguta M, Mazvimavi K, Craufurd P, Dorward P. 2012. Farmer perceptions on climate change and variability in semi-arid Zimbabwe in relation to climatology evidence. African Crop Science Journal, 20: 317-335.

Muchow RC, Carberry PS. 1989. Environmental control of phenology and leaf growth in a tropically adapted maize. Field Crops Research, 20: 221-236.

Muchow R, Davis R. 1988. Effect of nitrogen supply on the comparative productivity of maize and sorghum in a semi-arid tropical environment II. Radiation interception and biomass accumulation. Field Crops Research, 18: 17-30.

Muchow RD, Hammer GL, Carberry PS. 1991. Optimising crop and cultivar selection in response to climatic risk. In: Muchow RC, Bellamy JA. (eds.). Climatic Risk in Crop Production: Models and Management for the Semiarid Tropics and Subtropics. CAB International, Wallingford, pp. 235-262.

Muchow R, Hammer G, Vanderlip R. 1994. Assessing climatic risk to sorghum production in water-limited subtropical environments II. Effects of planting date, soil water at planting, and cultivar phenology. Field Crops Research, 36: 235-246.

Mueller DJ. 1986. Measuring Social Attitudes. A Handbook for Researchers and Practitioners. Teachers College Press, New York.

Mueller ND, Gerber JS, Johnston M, Ray DK, Ramankutty N, Foley JA. 2012. Closing yield gaps through nutrient and water management. Nature, 490: 254-257.

Mulat D, Fantu G, Tadele F. 2006. Agricultural Development and Food Security in Sub-Saharan Africa (SSA), Building the Case for More Public Support, The Ethiopian Case Study, FAO, Rome.

Mulat D, Teketel A. 2003. Ethiopian agriculture: macro and micro perspective. Afrint Macro Study (final) (mimeo.). Department of Business Administration, Addis Ababa.

Mupangwa W, Love D, Twomlow S. 2006. Soil–water conservation and rainwater harvesting strategies in the semi-arid Mzingwane Catchment, Limpopo Basin, Zimbabwe. Physics and chemistry of the Earth, Parts A/B/C, 31: 893-900.

Murovhi N, Materechera S. 2013. Growth and nutrient uptake by maize (*Zea mays* L.) in a soil amended with leaf litter from sub-tropical fruit trees in Mpumalanga province, South Africa. Journal of Food, Agriculture and Environment, 11: 427-432.

Namakka A, Abubakar IU, Sadik IA, Sharifai AI, Hassas AH. 2008. Effect of sowing date and nitrogen level on yield and yield components of two extra early maize varieties (*Zea mays* L.) in Sudan savanna of Nigeria. ARPN Journal of Agricultural & Biological Science, 3: 1-5.

Ncube B, Dimes J, Twomlow S, Mupangwa W, Giller K. 2007. Raising the productivity of smallholder farms under semi-arid conditions by use of small doses of manure and nitrogen: a case of participatory research. Nutrient Cycling in Agroecosystems, 77: 53-67.

Ncube B, Manzungu E, Love D, Magombeyi M, Gumbo B, Lupankwa K. 2010. The challenge of integrated water resource management for improved rural livelihoods: Managing risk, mitigating drought and improving water productivity in the water scarce Limpopo Basin.

NeSmith D, Ritchie J. 1992. Short-and long-term responses of corn to a pre-anthesis soil water deficit. Agronomy Journal, 84: 107-113.

Newig J. 2007. Does public participation in environmental decisions lead to improved environmental quality. Communication, Cooperation, Participation. Research and Practice for a sustainable Future, 1: 51-71.

Nicholls N. 1999. Cognitive illusions, heuristics, and climate prediction. Bulletin of the American Meteorological Society, 80: 1385-1397.

Nigussie M, Mohammed H, Sebokssa G, Bogale G, Beyene Y, Hailemichael S, Hadis A. 2001. Maize improvement for drought stressed areas of Ethiopia. In: Nigussie M, Tanner D, Twumasi-Afriyie S. (eds.). Proceedings of the Second National Maize Workshop of Ethiopia, “Enhancing the Contribution of Maize to Food Security in Ethiopia”, 12-16 November 2001, Addis Ababa, Ethiopia, EARO, CIMMYT, pp. 15-26.

Nix HA. 1984. Minimum data sets for agrotechnology transfer. In: Proceedings of the international symposium on minimum data sets for agrotechnology transfer, ICRISAT, Patancheru, Andhra Pradesh, India, pp. 181-188

Nkonya E, Schroeder T, Norman D. 1997. Factors affecting adoption of improved maize seed and fertiliser in northern Tanzania. Journal of Agricultural Economics, 48: 1-12.

NMA (National Meteorological Agency). 2007. Climate Change National Adaptation Programme of Action (NAPA) of Ethiopia. Technical Report, United Nations Development Program (UNDP), NMA, Ethiopia, Addis Ababa.

NMSA (Ethiopian National Meteorological Services Agency). 2001. Initial national communication of Ethiopia to the United Nations Framework Convention on Climate Change (UNFCCC), NMSA, Addis Ababa, Ethiopia.

NMSA (Ethiopian National Meteorology Service Agency). 1996. Climatic and Agro climatic Resources of Ethiopia. Vol. 1, No. 1. NMSA, Addis Ababa, Ethiopia.

Norman D. 2000. Farm management and the farming systems approach. In: Collinson M. (ed.). A history of farming systems research. CABI Publishing, Wallingford, UK, pp. 293-299.

Nziguheba G, Palm CA, Berhe T, Denning G. et al. 2010. The African Green Revolution: results from the Millennium Villages project. Advances in Agronomy, 109: 75-115.

O'Brien R. 1998. An overview of the methodological approach of action research. Faculty of Information Studies, University of Toronto.

Ojiem JO, de Ridder N, Vanlauwe B, Giller KE. 2006. Socio-ecological niche: A conceptual framework for integration of legumes in smallholder farming systems. International Journal of Agricultural Sustainability, 4: 79-93.

Okalebo J, Othieno C, Woomer P, Karanja N, Semoka J, Bekunda M, Mugendi D, Muasya R, Bationo A, Mukhwana E. 2006. Available technologies to replenish soil fertility in East Africa. Nutrient Cycling in Agroecosystems, 76: 153-170.

Okali C, Sumberg J, Farrington J. 1994. Farmer participatory research: rhetoric and reality. Intermediate Technology Publications, London.

Olsen S, Sommers L, Page A. 1982. Methods of soil analysis. Part 2. Agronomy Monograph No. 9, American Society of Agronomy, Crop Science Society of America, Soil Science Society of America, Madison, Wisconsin, USA, pp. 403-430.

Onduru D, De Jager A, Gachini G, Diop J. 2001. Exploring new pathways for innovative soil fertility management in Kenya. Managing Africa's Soils No. 25. International Institute for Environment and Development, London, UK.

Orlove B, Roncoli C, Kabugo·M, Majugu A. 2010. Indigenous climate knowledge in southern Uganda: the multiple components of a dynamic regional system. Climate Change, 100: 243-265.

Ortiz O, Orrego R, Pradel W, Gildemacher P, Castillo R, Otiniano R, Gabriel J, Vallejo J, Torres O, Woldegiorgis G. 2011. Incentives and disincentives for stakeholder involvement in participatory research (PR): lessons from potato-related PR from Bolivia, Ethiopia, Peru and Uganda. International Journal of Agricultural Sustainability, 9: 522-536.

Osbahr H, Dorward P, Stern R, Cooper S. 2011. Supporting agricultural innovation in Uganda to respond to climate risk: linking climate change and variability with farmer perceptions. Experimental Agriculture, 47: 293-316.

Otsuka K, Yamano T, Place F. 2011. Conclusion: toward the transformation of agriculture in East Africa. In: Yamano T, Otsuka K, Place F. (eds.). Emerging Development of Agriculture in East Africa. Springer, The Netherlands, pp. 203-210.

Packham R. 2011. The farming systems approach. Shaping Change: Natural Resource Management Agriculture and the Role of Extension. Australia Pacific Extension Network, pp. 32-49.

Pain R, Francis P. 2003. Reflections on participatory research. Area, 35: 46-54.

Pandey R, Maranville J, Bako Y. 2001. Nitrogen fertilizer response and use efficiency for three cereal crops in Niger. Communications in soil science and plant analysis, 32: 1465-1482.

Pandey S, Bhandari H. 2009. Drought, Coping Mechanisms and Poverty: Insights from Rainfed Rice Farming in Asia. Seventh Discussion Papers, Asia and the Pacific Division, IFAD.

Penning de Vries FWT, Jansen DM, ten Berge HFM, Bakema, A. 1989. Simulation of Ecophysiological Processes of Growth in Several Annual Crops. Pudoc, Wageningen.

Power B, Rodriguez D, De Voil P, Harris G, Payero J. 2011. A multi-field bio-economic model of irrigated grain – cotton farming systems. Field Crop Research, 124: 171-179.

Pretty J. 1995. Participatory learning for sustainable agriculture. World development, 23: 1247-1263.

Priestley CHB, Taylor RJ. 1972. On the assessment of surface heat flux and evaporation using large-scale parameters. Monthly weather review, 100(2): 81-92.

Probert ME. 2004. A capability in APSIM to model P responses in crops. In: Delve RJ, Probert ME. (eds.). Modelling Nutrient Management in Tropical Cropping Systems. Proceedings No. 114, ACIAR, pp. 92-100.

Probert ME, Dimes J, Keating B, Dalal R, Strong W. 1998. APSIM's water and nitrogen modules and simulation of the dynamics of water and nitrogen in fallow systems. Agricultural Systems, 56: 1-28.

Quinn CH, Hubi M, Kiwasila H, Lovett JC. 2003. Local perception of risk to livelihood in semi-arid Tanzania. Journal of Environmental Management, 68: 111-119.

Rabbinge R, Leffelaar PA, van Latesteijn HC. 1994. The role of systems analysis as an instrument in policy making and resource management. In: Goldsworthy PR, Penning de Vries FWT. (eds.). Opportunities, Use, and Transfer of Systems Research Methods in Agriculture to Developing Countries. Dordrecht, Kluwer Academic, The Netherlands, pp. 67-79.

Ransom JK, Regassa T, Nigussie M. 1997. Use of simulation models to predict the optimum duration of maize cultivars adapted to the Rift Valley of Ethiopia. In: Edmeades GO, Bänziger M, Mickleson, HR, Pena Valdiva GB. (eds.). Developing Drought- and Low-N

Tolerant Maize. Proceedings of a Symposium, March 25-29, 1996, El Batan, Mexico, CIMMYT, pp. 96-98.

Rao K, Ndegwa W, Kizito K, Oyoo A. 2011. Climate variability and change: Farmer perceptions and understanding of intra-seasonal variability in rainfall and associated risk in semi-arid Kenya. Experimental Agriculture, 47: 267-291.

Rashid S, Getnet K, Lemma S. 2010. Maize value chain potential in Ethiopia: Constraints and opportunities for enhancing the system. International Food Policy Research Institute working paper. USA, Washington, DC, IFPRI.

Reddy M, Georgis K. 1993. Dryland farming research in Ethiopia: review of the past and thrust in the nineties, Ethiopia, Addis Ababa, Ethiopia, Institute of Agricultural Research (IAR).

Rembold F, Stefano C, Nori M, Ferrari GA. 2000. Use of aerial photographs, Landsat TM imagery and multidisciplinary field survey for land-cover change analysis in the lakes region (Ethiopia). International Journal of Applied Earth Observation and Geoinformation, 2: 181-189.

Reynolds JF, Acock B. 1997. Modularity and genericness in plant and ecosystem models. Ecological Modelling, 94: 7-16.

Reynolds M, Holwell S. (eds.). 2010. Systems Approaches to Managing Change: a Practical Guide. Springer, London.

Ritchie JT. 1972. Model for predicting evaporation from a row crop with incomplete cover. Water Resources Research, 8: 1204-1213.

Ritchie JT. 1991. Specifications of the ideal model for predicting crop yield. In: Muchow RC, Bellamy JA. (eds.). Climatic Risk in Crop Production: Model and Management for the Semi-Arid Tropic and Subtopic. Proc. Intl. Symp. S. Lucia, Brisbane, Queensland, Australia 2-6 July, 1990. CAB International, Wallingford, UK, pp. 97-122.

Ritchie JT, Kiniry R, Jones CA, Dyke PT. 1986. Model inputs. In: Jones CA, Kiniry JR. (eds.). CERES-Maize: A Simulation Model of Maize Growth and Development. Texas A&M University Press, College Station, pp. 37-48.

Ritchie JT, NeSmith DS. 1991. Temperature and crop development. In: Hanks J, Ritchie JT. (eds.). Modeling Plant and Soil Systems, Agronomy. Monograph No. 31, American Society of Agronomy, Crop Science Society of America, Soil Science Society of America, Madison, Wisconsin, USA, pp. 5-29.

Robertson MJ, Carberry PS, Lucy M. 2000. Evaluation of a new cropping option using a participatory approach with on-farm monitoring and simulation: a case study of spring-sown mungbeans. Australian Journal of Agricultural Research, 51: 1-12.

Robertson MJ, Sakala W, Benson T, Shamudzarira Z. 2005. Simulating response of maize to previous velvet bean (*Mucuna pruriens*) crop and nitrogen fertiliser in Malawi. Field Crops Research, 91: 91-105.

Rockström J. 2003. Water for food and nature in drought-prone tropics: Vapor Shift in rainfed agriculture. Philosophical Transactions of the Royal Society Biological Sciences, 358: 1997-2009.

Rockström J, Kaumbutho P, Mwalley J, Nzabi A, Temesgen M, Mawenya L, Barron J, Mutua J, Damgaard-Larsen S. 2009. Conservation farming strategies in East and Southern Africa: yields and rain water productivity from on-farm action research. Soil & Tillage Research, 103: 23-32.

Rodriguez D, Cox H, Power B. 2014. A participatory whole farm modelling approach to understand impacts and increase preparedness to climate change in Australia. Agricultural Systems, 126: 50-61.

Rodriguez D, Devoil P, Power B, Cox H, Crimp S, Meinke H. 2011. The intrinsic plasticity of farm businesses and their resilience to change. An Australian example. Field Crops Research, 124: 157-170.

Rodriguez D, de Voil P, Rufino MC, Odendo M, van Wijk MT. 2017. To mulch or to munch? Big modelling of big data. Agricultural Systems, 153: 32-42.

Rodriguez D, Sadras V. 2011. Opportunities from integrative approaches in farming systems design. Field Crops Research, 124: 137-141.

Röling N. 1990. The agricultural research-technology transfer interface: A knowledge systems perspective. In: Kaimowitz D (ed.). Making the link: Agricultural research and technology transfer in developing countries. Boulder, CO: Westview Press, pp. 1-42.

Röling N, Jiggins J. 1998. The ecological knowledge system. In: Röling N, Wagermakers MA. (eds.). Facilitating sustainable agriculture. Participatory learning and adaptive management in times of environmental uncertainty. Cambridge University Press, Cambridge, pp. 283-311.

Roman-Paoli E, Welch SM, Vanderlip RL. 2000. Comparing genetic coefficient estimation methods using the CERES-Maize model. Agricultural Systems, 65: 29-41.

Roncoli C. 2006. Ethnographic and participatory approaches to research on farmers' responses to climate predictions. Climate Research, 33: 81-99.

Roncoli C, Ingram K, Kirshen P. 2002. Reading the rains: Local knowledge and rainfall forecasting in Burkina Faso. Society & Natural Resources, 15: 409-427.

Rosell S, 2011. Regional perspective on rainfall change and variability in the central highlands of Ethiopia, 1978-2007. Applied Geography, 31: 329-338.

Rötter R, Dreiser C. 1994. Extrapolation of maize fertilizer trial results by using crop-growth simulation: results for Murang'a District, Kenya. In: Fresco LO, Stroosnijder L, Boume J, Van Keulen H. (eds.). The Future of the Land: Mobilising and Integrating Knowledge for Land Use Options. John Wiley and Sons, Chichester, UK, pp. 249-260.

Rötter R, Van Keulen H. 1997. Variations in yield response to fertilizer application in the tropics: II. Risks and opportunities for smallholders cultivating maize on Kenya's arable land. Agricultural Systems, 53: 69-95

Roxburgh CW, Rodriguez D. 2016. Ex-ante analysis of opportunities for the sustainable intensification of maize production in Mozambique. Agricultural Systems, 142: 9-22.

Rurinda J, Mapfumo P, van Wijk MT, Mtambanengwe F, Rufino MC, Chikowo R, Giller KE. 2013. Managing soil fertility to adapt to rainfall variability in smallholder cropping systems in Zimbabwe. Field Crops Research, 154: 211-225.

Rusike J, Twomlow S, Freeman H, Heinrich G. 2006. Does farmer participatory research matter for improved soil fertility technology development and dissemination in Southern Africa? International Journal of Agricultural Sustainability, 4: 176-192.

Sacks WJ, Deryng D, Foley JA, Ramankutty N. 2010. Crop planting dates: an analysis of global patterns. Global Ecology and Biogeography, 19: 607-620.

Sadras VO. 2004. Yield and water-use efficiency of water and nitrogen-stressed wheat crops increase with degree of co-limitation. European Journal of Agronomy, 21: 455-464.

Sadras VO, Angus JF. 2006. Benchmarking water-use efficiency of rainfed wheat in dry environments. Australian Journal of Agricultural Research, 57: 847-856.

Safriel U, Adeel Z. 2008. Development paths of drylands: thresholds and sustainability. Sustainability Science, 3: 117-123.

Safriel U, Adeel Z, Niemeijer D, Puigdefabregas J, White R, Lal R, Winslow M, Ziedler J, Prince S, Archer E. 2005. Dryland systems. Ecosystems and human well-being, current state and trends, 1: 625-658.

Sands DM. 1986. Farming systems research: clarification of terms and concepts. Experimental Agriculture, 22: 87-104.

Saseendran SA, Ahuja LR, Ma L, Timlin DJ, Stockle CO, Boote KJ, Hoogenboom G. 2008. Current water deficit stress simulations in selected agricultural system simulation models. In: Ahuja LR, Reddy VR, Saseendran SA, Yu Q. (eds.). Response of Crops to Limited Water: Understanding and Modeling Water Stress Effects on Plant Growth Processes. American Society of Agronomy. Crop Science Society of America, Soil Science Society of America, Madison, WI, USA, pp. 1-38.

Saseendran SA, Ma L, Nielsen D, Vigil M, Ahuja L. 2005. Simulating planting date effects on corn production using RZWQM and CERES-Maize models. Agronomy Journal, 97: 58-71.

Schnier HF, Recke H, Muchena FN, Muriuki AW. 1997. Towards a practical approach to fertiliser recommendations for food crop production in smallholder farms in Kenya. Nutrient Cycling in Agroecosystems, 47: 213-226.

Schouwenaars JM. 1988. Rainfall irregularity and sowing strategies in Southern Mozambique. Agricultural water management, 13(1): 49-64.

Schwartz B, Sharpe K. 2006. Practical Wisdom: Aristotle meets Positive Psychology. Journal of Happiness Studies, 7: 377-395.

Scoones I, Thompson J. 1994. Knowledge, power and agriculture. Towards a theoretical understanding. In: Scoones I, Thompson J. (eds.). Beyond farmer first: Rural people's knowledge, agricultural research and extension practice. Intermediate Technology Publications, London, pp. 16-32.

Seleshi Y, Camberlin P. 2006. Recent changes in dry spell and extreme rainfall events in Ethiopia. Theoretical and Applied Climatology, 83: 181-191.

Seleshi Y, Zanke U. 2004. Recent changes in rainfall and rainy days in Ethiopia. International Journal of Climatology, 24: 973-983.

Senay GB, Verdin J. 2003. Characterization of yield reduction in Ethiopia using a GIS-based crop water balance model. Canadian Journal of Remote Sensing, 29: 687-692.

Seymour E, Wickes R. 2011. Using Monitoring and Evaluation for Continuous Improvement of Rainfed Farming Systems. In: Tow P, Cooper I, Partridge I, Birch C. (eds.). Rainfed Farming Systems. Springer, Dordrecht, The Netherlands, pp. 757-776.

Shamudzarira Z, Robertson MJ. 2002. Simulating response of maize to nitrogen fertilizer in semi-arid Zimbabwe. Experimental Agriculture, 38: 79-96.

Shamudzarira Z, Waddington SR, Robertson M, Keating BA, Mushayi P, Chiduza C, Grace PR. 2000. Simulating N fertiliser responses in low-input farming systems 1. Fertiliser recovery and crop response. Risk Management Working Paper Series 00/05. Mexico, D.F., CIMMYT.

Sherrick BJ, Sonka ST, Lamb PJ, Mazzocco MA. 2000. Decision-maker expectations and the value of climate prediction information: conceptual considerations and preliminary evidence. Meteorological Applications, 7: 377-386.

Shiferaw B, Tesfaye T, Kassie M, Abate T, Prasanna BM, Menkir A. 2014. Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: Technological, institutional and policy options. Weather and Climate Extremes, 3: 67-79.

Sileshi G, Akinnifesi FK, Debusho LK, Beedy T, Ajayi OC, Mong'omba S. 2010. Variation in maize yield gaps with plant nutrient inputs, soil type and climate across sub-Saharan Africa. Field Crops Research, 116(1): 1-13.

Simane B, van Keulen H, Stol W, Struik PC. 1994. Application of a crop growth model (SUCROS-87) to assess the effect of moisture stress on yield potential of durum wheat in Ethiopia. Agricultural Systems, 44: 337-353.

Simmonds N. 1986. A short review of farming systems research in the tropics. Experimental agriculture, 22: 1-13.

Sinclair TR, Hammer GL, van Oosterom EJ. 2005. Potential yield and water-use efficiency benefits in sorghum from limited maximum transpiration rate. Functional Plant Biology, 32: 945-952.

Sinclair TR, Seligman NG. 1996. Crop modeling: from infancy to maturity. Agronomy Journal, 88: 698-704.

Singh BR, Singh DP. 1995. Agronomic and physiological responses of sorghum, maize, and pearl-millet to irrigation. Field Crops Research, 42: 57-67.

Slegers MFW. 2008. Exploring farmers' perceptions of drought in Tanzania and Ethiopia. PhD thesis. Tropical Resource Management Paper No. 93. Wageningen University, The Netherlands.

Smaling EMA, Stoorvogel JJ, de Jager A. 2002. Decision making on integrated nutrient management through the eyes of the scientist, the land-user and the policy maker. In: Vanlauwe B, Diels J, Sanginga N, Merckx R. (eds.). Integrated Plant Nutrient Management in sub-Saharan Africa: from Concept to Practice, CABI, Wallingford, UK, pp. 265-283.

Snapp SS, Blackie MJ, Donovan C. 2003. Realigning research and extension to focus on farmers' constraints and opportunities. Food Policy, 28: 349-363.

Snapp SS, Mafongoya PL, Waddington S. 1998. Organic matter technologies for integrated nutrient management in smallholder cropping systems of southern Africa. Agriculture, Ecosystems and Environment, 71: 185-200.

Snapp SS, Rohrbach DD, Simtowe F, Freeman HA. 2002. Sustainable soil management options for Malawi: Can smallholder farmers grow more legumes? Agriculture, Ecosystems and Environment, 91: 159-174.

Soler CMT, Sentelhas PU, Hoogenboom G. 2007. Application of the CSM-CERES-maize model for planting date evaluation and yield forecasting for maize grown off-season in a subtropical environment. European Journal of Agronomy, 27: 165-177.

Song Y, Birch C, Qu S, Doherty A, Hanan J. 2010. Analysis and Modelling of the Effects of Water Stress on Maize Growth and Yield in Dryland Conditions. Plant Production Science, 13: 199-208.

Sorensen I, Stone P, Rogers B. 2000. Effect of sowing time on yield of a short and a long season maize hybrid. Agronomy New Zealand, 30: 63-66.

Sowell RS, Ward RC. 1998. Modeling processes and operations with linear programming. In: Peart RM, Curry RB. (eds.). Agricultural Systems Modeling and Simulation, Marcel Dekker, New York, pp. 113-156.

Spielman DJ, Byerlee D, Alemu D, Kelemework D. 2010. Policies to promote cereal intensification in Ethiopia: the search for appropriate public and private roles. Food Policy, 35: 185-194.

Stackhouse Jr P. 2010. Prediction of worldwide energy resources. NASA, Washington, DC, USA. http://power.larc.nasa.gov/. (Accessed 12 March 2014).

Stapper M. 1986. Modelling plant growth and development. In: Plant Virus Epidemics: Monitoring, Modelling and Predicting Outbreaks, Academic Press, Sydney, Australia, pp. 249-272.

Stapper M, Harris HC. 1989. Assessing the productivity of wheat genotypes in a Mediterranean climate, using a crop-simulation model. Field Crops Research, 20: 129-152.

Stehr N. 1997. Trust and climate. Climate Research, 8: 163-169.

Stehr N, von Storch H. 1995. The social construct of climate and climate change. Climate Research, 5: 99-105.

Stepanek JC. 1999. Lessons from Ethiopia's High-Input Technology Promotion Program: How the Organization of the Fertilizer Subsector Affects Maize Productivity. PhD dissertation, Michigan State University.

Stern R, Cooper PJ. 2011. Assessing climate risk and climate change using rainfall data – A case study from Zambia. Experimental Agriculture, 47: 241-266.

Stewart BA, Koohafkan P, Ramamoorthy K, Peterson G, Unger P, Payne W. 2006. Dryland agriculture defined and its importance to the world. In: Peterson GA, Unger PW, Payne WA. (eds.). Dryland Agriculture. Agronomy Monograph 23, American Society of Agronomy, Crop Science Society of America, Soil Science Society of America, Madison, Wisconsin, USA, pp. 1-26.

Stöckle CO, Donatelli M, Nelson R. 2003. CropSyst, a cropping systems simulation model. European Journal of Agronomy, 18: 289-307.

Stoneham G, Eigenraam M, Ridley A, Barr N. 2003. The application of sustainability concepts to Australian agriculture: an overview. Animal Production Science, 43: 195-203.

Sutherland A. 1998. Participatory research in natural resources. Socio-economic Methodologies. Best Practice Guidelines. Chatham, UK, Natural Resources Institute.

Tanner CB, Sinclair TR. 1983. Efficient water use in crop production: Research or Re-Search? In: Taylor HM, Jordan WR, Sinclair TR. (eds.). Limitations to Efficient Water Use in Crop Production, Chapter 1A. American Society for Agronomy, pp. 1-27.

Temesgen M, Hoogmoed W, Rockstrom J, Savenije H. 2009. Conservation tillage implements and systems for smallholder farmers in semi-arid Ethiopia. Soil & Tillage Research, 104: 185-191.

Tenywa MM, Bekunda M. 2009. Managing soils in Sub-Saharan Africa: Challenges and opportunities for soil and water conservation. Journal of Soil &Water Conservation, 64: 44A-48A.

Tesfaye K, Walker S. 2004. Matching of crop and environment for optimal water use: the case of Ethiopia. Physics & Chemistry of the Earth, 29: 1061-1067.

Thierfelder C, Wall PC. 2011. Reducing the Risk of Crop Failure for Smallholder Farmers in Africa through the Adoption of Conservation Agriculture. In: Bationo A, Waswa B, Okeyo JMM, Maina F, Kihara JM. (eds.). Innovations as Key to the Green Revolution in Africa. Springer, The Netherlands, pp. 1269-1277.

Thomas DSG, Twyman C, Osbahr H, Hewitson B. 2007. Adaptation to climate change and variability: farmer responses to intra-seasonal precipitation trends in South Africa. Climate Change, 83: 301-322.

Thornton PK, Herrero M. 2001. Integrated crop-livestock simulation models for scenario analysis and impact assessment. Agricultural Systems, 70: 581-602.

Thornton PK, Jones PG, Ericksen PJ, Challinor AJ. 2011. Agriculture and food systems in sub-Saharan Africa in a 4°C+ world. Philosophical Transactions of the Royal Society A: Mathematical, Physical & Engineering Sciences, 369: 117-136.

Thornton PK, Jones PG, Owiyo TM, Kruska RL, Herrero M, Kristjanson P, Notenbaert A, Bekele N, Omolo A, Orindi V, Ochieng A, Otiende B, Bhadwal S, Anantram K, Nair S, Kumar V, Kelkar U. 2006. Mapping Climate Vulnerability and Poverty in AFRICA: Report to the Department for International Development. ILRI, Nairobi, Kenya.

Thornton PK, Saka A, Singh U, Kumwenda J, Brink J, Dent J. 1995. Application of a maize crop simulation model in the central region of Malawi. Experimental Agriculture, 31: 213-226.

Timsina J, Humphreys E. 2006. Performance of CERES-Rice and CERES-Wheat models in rice-wheat systems: A review. Agricultural Systems, 90: 5-31.

Tittonell P, Giller KE. 2013. When yield gaps are poverty traps: The paradigm of ecological intensification in African smallholder agriculture. Field Crops Research, 143: 76-90.

Tittonell P, Muriuki A, Shepherd KD, Mugendi D, Kaizzi KC, Okeyo J, Verchot L, Coe R, Vanlauwe B. 2010. The diversity of rural livelihoods and their influence on soil fertility in agricultural systems of East Africa: A typology of smallholder farms. Agricultural Systems, 103: 83-97

Tittonell P, Vanlauwe B, Corbeels M, Giller KE. 2008. Yield gaps, nutrient use efficiencies and response to fertilisers by maize across heterogeneous smallholder farms of western Kenya. Plant Soil, 313: 19-37.

Tittonell P, Vanlauwe B, Leffelaar PA, Rowe EC, Giller KE. 2005. Exploring diversity in soil fertility management of smallholder farms in western Kenya I. Heterogeneity at region and farm scale. Agriculture, Ecosystems & Environment, 110: 149-165.

Tittonell P, van Wijk MT, Rufino MC, Vrugt JA, Giller KE. 2007a. Analysing trade-offs in resource and labour allocation by smallholder farmers using inverse modelling techniques: a case study from Kakamega district, western Kenya. Agricultural Systems, 95: 76-95.

Tittonell P, Zingore S, van Wijk MT, Corbeels M, Giller KE. 2007b. Nutrient use efficiencies and crop responses to N, P and manure applications in Zimbabwean soils: Exploring management strategies across soil fertility gradients. Field Crops Research, 100: 348-368.

Tow P, Cooper I, Partridge I, Birch C, Harrington L. 2011. Principles of a systems approach to agriculture. In: Tow P, Cooper I, Partridge I, Birch C. (eds.). Rainfed Farming Systems. Springer, Dordrecht, The Netherlands, pp. 3-43.

Townsley P. 1996. Rapid rural appraisal, participatory rural appraisal and aquaculture. FAO Fisheries technical report no. 358, Food and Agriculture Organization.

Tsimba R, Edmeades GO, Millner JP, Kemp PD. 2013. The effect of planting date on maize grain yields and yield components. Field Crops Research, 150: 135-144.

Twomlow S, Rohrbach D, Dimes J, Rusike J, Mupangwa W, Ncube B, Hove L, Moyo M, Mashingaidze N, Mahposa P. 2010. Micro-dosing as a pathway to Africa's Green Revolution: evidence from broad-scale on-farm trials. Nutrient Cycling in Agroecosystems, 88: 3-15.

Twomlow S, Rohrbach D, Dimes J, Rusike J, Mupangwa W, Ncube B, Hove L, Moyo M, Mashingaidze N, Mahposa P. 2011. Micro-dosing as a pathway to Africa's Green Revolution: evidence from broad-scale on-farm trials. Innovations as Key to the Green Revolution in Africa. Springer, pp. 1101-1113.

UNEP (United Nations Environmental Program). 1992. World atlas of desertification. UNEP, Nairobi, Kenya.

USDA. 1972. National engineering handbook. Hydrology, Section 4. Soil Conservation Service, USDA, Washington DC, USA.

Valbuena D, Bregt AK, McAlpine C, Verburg PH, Seabrook L. 2010. An agent-based approach to explore the effect of voluntary mechanisms on land use change: a case in rural Queensland. Australia Journal of Environmental Management, 91(12): 2615-2625.

Van Eijk T. 2000. Holism and FSR. In: Collinson M. (ed.). A history of farming systems research. FAO and CABI Publishing, Wallingford, UK, pp. 323-334.

Van Ginkel M, Sayer J, Sinclair F, Aw-Hassan A, Bossio D, Craufurd P, El Mourid M, Haddad N, Hoisington D, Johnson N, Velarde CL, Mares V, Mude A, Nefzaoui A, Noble A, Rao KPC, Serraj R, Tarawali S, Vodouhe R, Ortiz R. 2013. An integrated agro-ecosystem and livelihood systems approach for the poor and vulnerable in dry areas. Food Security, 5: 751-767.

Van Ittersum MK, Cassman KG, Grassini P, Wolf J, Tittonell P, Hochman Z. 2013. Yield gap analysis with local to global relevance – a review. Field Crops Research, 143: 4-17.

Van Ittersum M, Leffelaar P, Van Keulen H, Kropff M, Bastiaans L, Goudriaan J. 2003. On approaches and applications of the Wageningen crop models. European Journal of Agronomy, 18: 201-234.

Van Ittersum M, Rabbinge R. 1997. Concepts in production ecology for analysis and quantification of agricultural input-output combinations. Field Crops Research, 52: 197-208.

Van Keulen H, Penning de Vries, FWT, Drees, EM. 1982. A summary model for crop growth. Simulation of Plant Growth and Crop Production. Simulation Monographs. Pudoc, Wageningen, The Netherlands, pp. 87-98.

Vanlauwe B, Kihara J, Chivenge P, Pypers P, Coe R, Six J. 2011. Agronomic use efficiency of N fertilizer in maize-based systems in sub-Saharan Africa within the context of integrated soil fertility management. Plant Soil, 339: 35-50.

Van Wijk M, Rufino M, Enahoro D, Parsons D, Silvestri S, Valdivia R, Herrero M. 2014. Farm household models to analyse food security in a changing climate: a review. Global Food Security, 3: 77-84.

Van Wijk M, Tittonell P, Rufino M, Herrero M, Pacini C, de Ridder N, Giller KE. 2009. Identifying key entry-points for strategic management of smallholder farming systems in sub-Saharan Africa using the dynamic farm-scale simulation model NUANCES-FARMSIM. Agricultural Systems, 102: 89-101.

Vayssières J, Bocquier F, Lecomte P. 2009. GAMEDE: A global activity model for evaluating the sustainability of dairy enterprises. Part II–Interactive simulation of various management strategies with diverse stakeholders. Agricultural Systems, 101: 139-151.

Von Braun J, Olofinbiyi T. 2007. Famine and food security in Ethiopia. In: Pinstrup-Andersen P, Cheng F. (eds.). Food policy for developing countries: The role of government in the global food system, Ithaca, NY, Cornell University, pp. 1-11.

VSN International. 2010. GenStat for windows 14 th Edition, VSN International Ltd, Hemel Hempstead, UK.

Wallach D, Makowski D, Jones JW, Brun F. 2014. Basics of Agricultural System Models. In: Working with dynamic crop models: methods, tools and examples for agriculture and environment 2nd ed. Elsevier, Academic Press, pp. 3-44.

Wang E, Engel T. 2000. SPASS: a generic process-oriented crop model with versatile windows interfaces. Environmental Modelling & Software, 15: 179-188.

Wang E, Robertson M, Hammer G, Carberry P, Holzworth D, Meinke H, Chapman S, Hargreaves J, Huth N, McLean G. 2002. Development of a generic crop model template in the cropping system model APSIM. European Journal of Agronomy, 18: 121-140.

Wang J, Wang E, Yang X, Zhang F, Yin H. 2012. Increased yield potential of wheat-maize cropping system in the North China Plain by climate change adaptation. Climatic change, 113: 825-840.

Weber GV, Chude J, Pleysier, Oikeh S. 1995. On-farm evaluation of nitrate-nitrogen dynamics under maize in the northern Guinea savanna of Nigeria. Experimental Agriculture, 31: 333-344.

Whitbread A, Robertson M, Carberry P, Dimes J. 2010. How farming systems simulation can aid the development of more sustainable smallholder farming systems in southern Africa. European Journal of Agronomy, 32: 51-58.

White JW, Grace PR. 1998. Directions in modeling wheat and maize for developing countries: proceedings of a workshop: vol. 1, 4-6 May 1998, El Batán, Mexico, CIMMYT.

Wilhite DA, Glantz MH. 1985. Understanding the drought phenomenon: the role of definitions. Water international, 10: 111-120.

Wilson D, Muchow R, Murgatroyd C. 1995. Model analysis of temperature and solar radiation limitations to maize potential productivity in a cool climate. Field Crops Research, 43: 1-18.

Woodward SJR, Romera AJ, Beskow WB, Lovatt SJ. 2008. Better simulation modelling to support farming systems innovation: Review and synthesis. New Zealand Journal of Agricultural Research, 51: 235-252.

World Bank. 2006. Managing Water Resources to Maximise Sustainable Growth: A Country Water Resources Assistance Strategy for Ethiopia. Washington, DC, World Bank.

World Bank. 2008. Agriculture for Development: World Development Report 2008. The World Bank, Washington, DC.

WWAP (World Water Assessment Programme). 2009. The United Nations World Water Development Report 3: Water in a Changing World. Paris: UNESCO, and London: Earth scan.

Xie Y, Kiniry JR, Nedbalek V, Rosenthal WD. 2001. Maize and sorghum simulations with CERES-maize, SORKAM, and ALMANAC under water-limiting conditions. Agronomy Journal, 93: 1148-1155.

Xiong W, Holman I, Conway D, Lin E, Li Y. 2008. A crop model cross calibration for use in regional climate impacts studies. Ecological Modelling, 213: 365-380.

Xu Z, Guan Z, Jayne TS, Black R. 2009. Factors influencing the profitability of fertilizer use on maize in Zambia. Agricultural Economics, 40: 437-446.

Yang HS, Dobermann A, Lindquist JL, Walters DT, Arkebauer TJ, Cassman KG. 2004. Hybrid-maize–a maize simulation model that combines two crop modeling approaches. Field Crops Research, 87: 131-154.

Yimer F, Abdelkadir A. 2010. Soil property changes following conversion of acacia woodland into grazing and farmlands in the Rift Valley area of Ethiopia. Land Degradation & Development, 22: 425-431.

Yin X, van Laar HH. 2005. Crop Systems Dynamics: an ecophysiological simulation model of genotype-by-environment interactions. Wageningen Academic Publishers, Wageningen, the Netherlands.

Yonas Y. 2001. Managing fragile ecosystem, combating desertification and drought. In: Hecktett T. (ed.). Ethiopian Civil Society Preparation for Rio 10. The Forum for Environment. Heinrich Boll Foundation, Addis Ababa, Ethiopia.

Zavale H, Mabaya E, Christy R. (eds.). 2005. Adoption of improved maize seed by smallholder farmers in Mozambique. Staff Paper, Cornell University, Department of Applied Economics and Management, Cornell University.

Zeleke TB, Grevers MCJ, Si BC, Mermut AR, Beyene S. 2004. Effect of residue incorporation on physical properties of the surface soil in the South Central Rift Valley of Ethiopia. Soil & Tillage Research, 77: 35-46.

Zewdie E. 2004. Characterization and genesis of some soils of the Ethiopian Rift Valley showing andic properties. Ethiopian Journal of Natural Resources, 6: 215-235.

Ziervogel G, Downing TE. 2004. Stakeholder networks: improving seasonal climate forecasts. Climatic change, 65: 73-101.

Zingore S, Murwira HK, Delve RJ, Giller KE. 2007a. Soil type, management history and current resource allocation: three dimensions regulating variability in crop productivity on African smallholder farms. Field Crops Research, 101: 296-305.

Zingore S, Murwira HK, Delve RJ, Giller KE. 2007b. Influence of nutrient management strategies on variability of soil fertility, crop yields and nutrient balances on smallholder farms in Zimbabwe. Agriculture, Ecosystems & Environment, 119: 112-126.

Appendix

Focus Group Discussion Questions

This focus group interview is aimed at understanding what farmers think and do regarding the impact of climate variability on their farming activities. We are interested to document the kind of seasonal forecasting they use, their sources of climate information and how their understanding of climate variability translates into farm management decisions and actions. The following questions will guide the discussions.

Part 1: Perceptions, attitudes and knowledge about climate variability

1. How do you describe the variation in climate, for example how rains are different from one year to another year?

   Seasonality diagramming: - *(These will be done with the use of stones, sticks or different coloured seeds to represent month's quantities of historical rainfall as back as farmers can remember)*

   a. In what ways does rainfall vary from year to year? In your opinion, has there always been variation from year to year in the rains?

   b. Is rainfall becoming more variable or less?

   c. Do you see any patterns in variation from year to year? Does one event usually follow another one ***(e.g., dry season occurs every five years)***? Are the patterns changing? How are they changing?

2. How is rainfall affecting maize production? Do you think the seasonal rainfall is reliable for maize production?

   a. From your experience, what do you consider to be a good, an average and a bad season for growing maize? ***(i.e., with respect to on-set of rain, seasonal rainfall amount, seasonal rainfall distribution, dry-spells, or others)***

   b. How often do you have bad seasons for maize? Are they becoming more or less frequent?

3. What other kinds of climate variability might there be such as in temperature, wind?

   a. In what ways does variability in temperature and wind affect maize production?

b. What extreme weather events have you experienced? What happened? In your view**,** how would you describe extreme weather/climatic events? ***(Refer to those years stand out in your memory and describe featuring characteristics of extreme events).***

Part 2: Perception, attitude and knowledge of climate risk and key management decision influenced by climate

4. What are your maize and other major crops yields during good, average and bad seasons? ***e.g., crop yield in kilogram per kert* (*=quarter of a hectare)***

a. How do you rate the rainfall seasons for maize production during the last 20 years?

b. What is the lowest, most likely and the highest yield of maize crop in the last 20 years? How often have they occurred?

c. In what ways are your maize crops affected by extreme events such as drought and flood?

5. What methods have you used to deal with climate variability? ***(e.g., land allocated for different crops, sowing date, planting density, crop or cultivar selection etc.)***

a. Which key management decisions in your farm activities are influenced by climate variability and adverse weather events?

b. In your opinion, do you think your methods are adequate to face the problem of existing climate variability?

Part 3: Awareness and use of seasonal climate information

6. Do you use forecasts to estimate what season lies ahead? How long have you been using the forecasts?

a. Have you used climate forecast information issued by the National Metrological Service (NMA)? What do you understand by the terms: above-normal (A), normal (N) and below normal (B) rainfall? How useful was it?

b. What other methods have you used to forecast what season lies ahead? (***Please describe any belief, local indicators/signals or any things that you can observe)***

c. How do NMA forecasts differ from other methods of weather forecasting? How are they similar? Do they conflict? Which is better and why?

7. How do you apply the climate forecast information in tailoring your management decisions?
   a. Can you explain how you applied any aspect of other forecast methods in making farm decision?
   b. Which parts of the NMA seasonal climate forecast information have helped for your farm activity? Explain how ***(e.g., on-set of rainfall, amount of seasonal rainfall etc.)***
   c. Have you ever decided not to apply seasonal forecasting? What did you do and what happened?
8. Do you combine your other knowledge with the NMA forecasting issued from NMA in your farm-decision making? If yes, how?
   a. If the forecasts are for a good season, how do you respond? Do others agree? Who would have a different response? What explanations do you have for the different responses? How is your farm level decision making process affected according to different farm typology ***(e.g., house-hold land holdings, wealth category)*** and/or bio-physical condition ***(e.g., soil fertility status, soil water holding capacity of the farm)***?
9. How accurate are the different types of climate forecast information***?*** And how reliable are they? ***(Seasonal climate forecast from NMA; traditional forecast method; a combination of forecast from NMA and traditional forecast method).***
10. Will more advanced seasonal climate forecasting aid your farm decision making in future?
    a. How could the seasonal forecasting be improved to best suit your needs in the future?
11. How do you plan to change your farming methods if seasons keep shifting as you have observed?

Key-informants Questionnaire

This key informant interview questionnaire will be administered to a selected group of people who are especially knowledgeable or experienced about the issue and are willing to share their knowledge. The interview will be conducted in a face to face setting which allows the researcher to seek new insights, ask questions, and assess phenomena in different perspectives. A broad range of insights about farmers' attitudes, perceptions and knowledge of past climate variablity will be sought, as well as how their understanding of climate variability translates into farm management decisions and actions. The kind of seasonal forecasting they are using and the value of seasonal climate information in guiding their key management decision will be assessed and documented.

Part 1: Respondent information, farm characterstics and farm experience

1. Location of farm (coordinate):____________Village___________District____________
   a. Gender_________ Age____________ level of education______________
   b. How long have you been farming?___________years
   c. What is the total size of the land you farm?_________hectare (ha)
   d. What crops do you grow?__________How long have you planting maize?______Years
   e. How much of your farm do you use to grow maize?_____ha
   f. Do you plant crops according to (soil type (local name of the soil), topographic position, or other criteria?________________________________.
   g. And on which of your farm plot do you grow maize?________________________.

Part 2: Perceptions, attitudes and knoweledge about climate variablity

2. How do you describe the climate variability of a season from one year to another year, orfrom one crop season to the next?

____

____

____

3. Was there a variability of seasonal rainfall '*Kiremt'* from one year to another year?

____

4. How do you describe your local historical *Kiremt* rainfall?

I. Variable
II. Some patterns (e.g., dry season or drought event usually follow after three years of wet season)
III. Not changed too much (more or less persistent rainfall)

5. How do you determine the start of the rainy season in your area? And how do farmers judge when rain is sufficient for planting?***Please explain***

6. What did you observe about the start date for the *Kiremt s*eason?

I. Variable
II. Some pattern (e.g., late start of the seasonal rainfall once in every three years)
III. Not changed too much

7. What did you observe about the duration of *Kiremt* season in the past years? ***Please explain***

8. How do you explain the duration of the *Kiremt* season?

I. Variable
II. Some pattern (e.g., shorter duration of the season once in three years)
III. Not changed too much

9. What does dry-spell mean to you? ***Please explain***

10. Did you observe any variablity in the occurence of dry-spells, i.e., periodswithout or very low rainfall during the cropping period?

    I. Variable
    II. Some pattern (e.g., long dry-spell during mid or late season once in three years)
    III. Not changed too much

11. How do you describe the level of temperature fluctuations over a long-time period? Did you observe unusually high or low temperatures that affected your crops? ***Please explain***

____

____

____

12. Did you observe any variablity in temperature? (***Months are considered as reference***)

    I. Variable
    II. Some pattern (e.g., high or low temperature once in five years)
    III. Not changed too much

Part 3: Perception, attitude and knowledge of climate risk and key management decisions influenced by climate

13. What factors do you think describe a poor, an average and a good rainfall season? ***(in terms of seasonal rainfall amount, on-set of rain and seasonal rainfall distribution and temperature or other criteria***).

____

____

How do you rate the rainfall seasons for maize production during the last 13 years?

Year	Low	Average	High	Comments
2011				
2010				
2009				
2008				
2007				
2006				
2005				
2004				
2003				
2002				
2001				
2000				
1999				

14. What is the lowest, most likely and the highest yield of maize crop? And how often they occur?

Lowest yield ***(Kilogram/Kert*)***	**How often in the last 10 years**	**Most likely yield** ***(Kilogram/Kert)***	**How often in the last 10 years**	**Highest yield** ***(Kilogram/Kert)***	**How often in the last 10 years**

Kert* (*=quarter of a hectare)

15. Which of the following is the most important climate risk that affects your maize yield? ***Prioritize according to their importance***

I. Late start of rainfall [ ]
II. Rain earlier than normal [ ]
III. Insufficient rainfall at the start of the season [ ]
IV. Early cessation of rainfall [ ]
V. Frequent heavy rainstorm [ ]
VI. Frequent dry-spells of more than one week [ ]
VII. Dry-spells around flowering [ ]
VIII. Dry-spell after flowering (during grain filling stage) [ ]
IX. Unusually low or high temperature [ ]
X. Other criteria [ ]

16. In your opinion, how do you describe extreme climatic events? And which of the years do you think there was an extreme weather event, since you started farming? ***Please explain***

____

____

a. Have you noticed any extremely unusual climatic event such as flood or drought since youstarted farming? ***Please explain***

____

____

17. Do you remember how climate affected your maize yield?And did that affect you?

Climate risk	**Number of times in the last 10 years**	**Consequence**	**Effect on crop yield/production (% change)**	**Adaptation strategy (what did you do?)**
Late start of rain				
Insufficient rain at the start of the season				
Early cessation of rainfall				
Frequent heavy rain				
Dry-spells around flowering				
Dry-spells after flowering				
Unusual high or low temperature				
Others (specify)				

18. Can you name in practice, the various methods you use to deal with impacts of climate variability? ***Please rate according to their importance***

I. Land allocation for maize and other crops [ ]

II. Timing of planting [ ]

III. Change in planting density [ ]

IV. Crop to plant [ ]

V. Change in cultivar selection (short cycle vs long cycle cultivar) [ ]

VI. More or less amount of fertiliser [ ]

VII. Timing of fertiliser application [ ]

VIII. Source of seed [ ]

IX. Growing of two or more crops [ ]

X. Use of moisture conservation method (tied-ridging) [ ]

XI. Others (specfy)_________________________ [ ]

19. In your opinion, do you think your methods are adequate to face the problem of existing climate variability? ***Please explain***

____

____

Part 4: Awarness and use of seasonal climate information

20. Do you use any form of weather or climate forecast? Yes [ ] No [ ]

21. If no, why not____
22. If yes, what kind forecast do you use about the local weather/climate condition?
    Only traditional forecasts [ ] Go to 24
    Only operational forecasts from NMA [ ] Go to 25
    Both forecast methods [ ] Go to 24

23. What methods or knowledge do you use in seasonal rainfall forecasting? ***Please explain***
____

____

____

24. Are you aware of climate forecasts issued by the National Metrological Service (NMA)?
    Yes [ ] No [ ]

25. If yes, what was the first year you ever received seasonal forecasts?
    ____

26. If no, why? ____

27. If you get the chance to receive seasonal climate forecasts issued from NMA, what specific climate-related information do you need for your key management decisions?

____

28. How do integrate the different forecasting methods in making farm decisions? ***Pleaseexplain***

____

____

____

29. Have you ever experienced any conflicting information between local knowledge and methods and NMA operational forecasting about the seasonal outlook?

____

____

30. Do you understand the information issued by NMA about the seasonal climate condition?

a. What do you understand by the terms: above-normal (A), normal (N) and below normal (B) ?

____

____

b. Which seasonal climate forecast information did help for your farm activity? (***e.g., on-set of rainfall, amount of seasonal rainfall orspecify________________________)***

31. Is seasonal forecast information provided from NMA suited to your needs?
Yes [ ] No [ ]

a. Please explain the relevance of climate-related information issued from NMA including what could be changed to better suit your needs?

____

____

____

32. Do you use any indicators/signals to foretell the seasonal climate condition? Give practical example how you applied any aspects of local indicators/signals in making farm decisions?

Indicators/Signals	**Condition of the season**					**What did you do?**
	dry	**wet**	**abnormally dry**	**abnormally wet**	**start of the season**	

33. How do you describe the accuracy of climate forecast information from NMA or using your traditional forecast using on scale of 1 to 4?

very accurate [4], fairly accurate [3], accurate [2], not accurate [1] , don't know [ ]

34. How best would you describe the accuracy of combined use of forecast from NMA and traditional methods on a scale of 1 to 4?

very accurate [4], fairly accurate [3], accurate [2], not accurate [1] , don't know[ ]

35. How do you rate the reliability of climate forecast information from NMA or traditional methods in making farm decisions using a scale of 1 to 4?

    very reliable [4], reliable [3], somehow [2], not reliable [1], don’t know [ ]

36. What of the reliability of climate forecast, by combining the traditional climate forecast information and from NMA?

    very reliable [4], reliable [3], somehow [2], not reliable [1], don’t know [ ]

37. Do you think advanced information on seasonal climate forecasts will generally aid your decisions?

1 [ ] (strongly disagree)	2 [ ]	3 [ ]	4 [ ] (strongly agree)

38. How do you plan to change your farming methods if seasons keep shifting as you have observed?

____

____

____